DOCTOR OF PHILOSOPHY

Dorsal hand feature analysis
an aid to forensic human identification

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Abbreviations

ACE-V: Analyse, Compare, Evaluate and Verify

AFSP: Association of Forensic Science Providers

ANOVA: Analysis of variance

BAHId: British Association for Human Identification

BF%: body fat percentage

BIA: Bioelectrical impedance analysis

C: clenched fist

C-AF: Controlled auto-focus

CAHId: Centre for Anatomy and Human Identification (University of Dundee)

CCTV: Closed Circuit Television

COA: Court of Appeal

COPINE: Combating Paedophile Information Networks

CSA: Child Sexual Abuse

DVN: Dorsal Venous Network

EER: Equal Error Rate

EV: Exposure value

FAR: False Acceptance Rate

FAVIAU: Forensic Audio, Video and Image Analysis Unit

FBI: Federal Bureau of Investigation

FIR: Far Infra-Red (light)

FNMR: False non-match rate

FMR: False match rate

FRE: Federal Rules of Evidence

FRR: False Rejection Rate

FSR: The Forensic Science Regulator
FSS: Forensic Science Service

HMA: His Majesty's Advocate

IR: Infra-red

LCD: liquid crystal display

LED: Light emitting diodes

LR: Likelihood Ratio

MC1R: melanocortin-1 receptor

MN: Melanocytic Nevi

MP: megapixel

NA: Network Analysis

NAS: National Academy of Sciences

NIR: Near Infra-Red (light)

NPIA: National Police Improvements Agency

PIN: personal identification number

SCRO: Scottish Criminal Record Office

SL: Solar Lentigines

SLR: Single lens reflex

Sp: semi-pronated hand

SUII: Scottish Universities Insight Institute

SWGIT: Scientific working group on Imaging Technology

UREC: University Research Ethics Council

URN: unique reference number

VL: visible light

VPA: Vein Pattern Analysis

VPP: Vein Pattern Project

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I would like to thank all my friends and colleagues in CAHId, past and present, who have made my time at CAHId memorable. To my friends back home who have provided the personal support, which has unquestionably kept me going throughout this process.

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Declaration

I (Miss Harriet Stratton) declare that I am the author of this thesis and that, unless otherwise stated, all references cited have been consulted by me. The work, of which this thesis is a record, has been completed by me. This thesis, or the work within it, has not been previously accepted for a higher degree, in this institution or any.

Harriet Stratton

Summary

The analysis of anatomical features on the dorsum of the hand has been utilised in forensic investigations for ascertaining anatomical similarities and differences between suspect and offender images, since 2007. This approach was introduced and developed by the team at CAHId, and has primarily been used in cases of child sexual abuse, where an image is discovered depicting the offence, and the perpetrator's hand visible in the image.

This form of evidence has been admitted as evidence on the premise of its strong anatomical underpinning. However, forensic techniques (both emerging and established) are increasingly being scrutinised for their reliability and validity with regards to legal admissibility. In response to this, the purpose of this research was to introduce a methodology to quantify the anatomical features most often used in the cases described, with the overriding aim of strengthening anatomical feature analysis as a reputable form of forensic evidence.

This thesis presents the results pertaining to establishing the reliability of data extraction from digital images, in terms of method repeatability. The variation of the veins and surface features was explored, with regard to influences from biological characteristics, and the investigation of whether images of poor quality (representing a forensic case image) lead to a loss of data, compared to the suspect image (usually of higher quality than the offender image).

The anatomical features (superficial vein patterns and surface features) were assessed both independently and in conjunction to establish whether more than one feature could be more discriminatory, than one.

The results of these analyses indicate that the method proposed in this study is reliable, when applied by one observer and by several. An overview of the vein pattern and surface feature variation is presented to give an indication of feature distribution across a sample population. Importantly, it was found that a significant level of anatomical information is lost when comparing images in standardised conditions with images in non-standardised conditions, representing forensic case images.

All results are extensively discussed in relation to relevant literatures and the applicability for use as a viable forensic technique with regards to current admissibility standards.

1 INTRODUCTION

1.1 Project significance and motivation

Research regarding the use of anatomical features on the dorsum of the hand has been an ongoing directive within the Centre for Anatomy and Human Identification (CAHId), University of Dundee, for the past seven years.

Research was prompted after Professor Black (CAHId) and the National Police Improvements Agency (NPIA) presented the assessment of the superficial vein patterns to the courts in 2007, whereby vein patterns were used as an aid to the identification of an offender from a still image, extracted from a video recording, depicting the alleged sexual abuse of a child.

In addition to the examination of the pattern created by the superficial veins on the dorsum of the hand, other anatomical features that are visible from a digital image of the dorsum of the hand have been employed, including areas of isolated pigmentation and scarring (Figure 1.1).

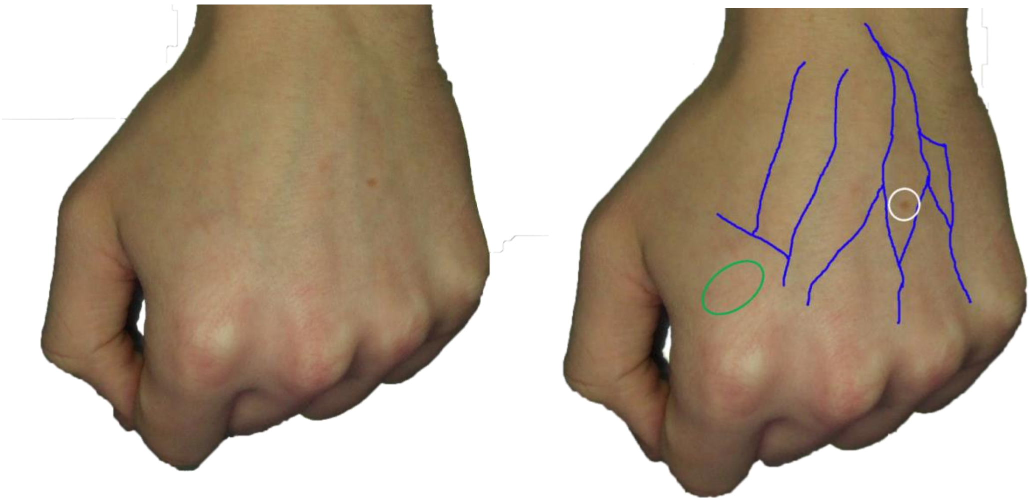


Figure 1.1 Examples of a raw image and after anatomical features are marked on a digital image of the dorsum of the hand. Blue: superficial veins, white: isolated area of pigmentation, green: scarring.

Post-2007 more than 26 forensic cases[1] have been investigated by the team at CAHId involving the assessment of digital images to establish similarities and differences in terms of anatomical structures, between two individuals, predominantly in cases involving the alleged sexual abuse of a child. In the majority of these cases, the evidence relating to the anatomical features has led to a change of plea and subsequent sentences range from 16 months to life imprisonment; one case led to the exposure of the largest paedophile ring in Scotland (Carrell, 2009). These facts are a credit to the work conducted by the team in CAHId regarding a crime that is becoming more frequently represented in our society.

In 1995, 3957 cautions or convictions for crimes involving the sexual abuse of children were reported (Grubin, 1998). In recent years, this number has increased to 21,493 (2011 – 2010) (Harker *et al.*, 2013), and furthermore to 23,663 cases of sexual offences against children being reported by the police in 2012 – 2013 (Jutte *et al.*, 2014). From these reported values, it cannot be inferred whether the increase in such crimes is due to increased reporting influenced by increased awareness, changes in policy that have

[1] This value only represents those cases which were taken to full investigation by CAHId, and does not include cases that were presented, but could not be accepted for various reasons.

encompassed a wider range of offences into the sexual offence category, or whether the actual incidence of such crimes has increased. Regardless, this rapidly growing area of criminal activity requires attention from research disciplines to ensure that these crimes are dealt with appropriately.

Crimes of this nature are unusual in that it is one of few crimes whereby the perpetrator records themselves committing the offence. In general terms, criminals seek to avoid identification with a view to evading punishment for their crimes, whereas in crimes of a sexual nature, perpetrators often seek a ‘trophy’; which can be in the form of photographic or video evidence (O’Donnell and Milner, 2007). The collection of such images have two purposes; they enable the perpetrator to ‘re-live’ the experience when not in the presence of the victim, often to facilitate sexual arousal of the so-called ‘collector’ (O’Donnell and Milner, 2007; Quayle, 2008). Furthermore, the images can be shared online so that the ‘collector’ can gain membership to illicit online groups and facilitate networking within the community of those with a similar sexually deviant appetite (O’Donnell and Milner, 2007; Quayle, 2008). With the advancement of the internet, the potential for child abuse images to be widely distributed has increased on an unimaginable scale (O’Donnell and Milner, 2007).

This scenario presents with two criminal offences; 1) the act of committing the physical abuse towards the victim, and 2) the downloading of the resultant images from the internet. These two offences carry differing penalties, and therefore when an individual is found in possession of indecent images of children, it is of utmost importance to ascertain whether that individual created the images and performed the abuse depicted, or whether the images were sourced from another location (i.e. downloaded from the internet).

The retrieved image(s) depicting child sexual abuse (CSA) becomes the evidence on which the identity of both the offender and the victim can be attempted to be established. These images often contain a region of the perpetrators anatomy, including the dorsum of the hand (Black *et al*., 2009; Ferguson and Raitt, 2013). It is the role of the forensic anthropologist to establish whether the suspect found in possession of the images, is the offender depicted within the image(s). This is performed on the basis of establishing similarities and differences between anatomical information seen on the offender within the criminal image, and images of the suspect which are captured in the custody suite (Meadows, 2011). This approach does not attempt to identify, but more importantly seeks to establish whether a suspect may be eliminated from the investigative process. In some cases, the similarities may be too great to confidently exclude the suspect, leaving the finder of facts (the jury) to decide the weight to be applied to this evidence (Ferguson and Raitt, 2013).

Further to establishing the identity of the offender, is the determination of the severity of the offence. Combating Paedophile Information Networks (COPINE) is a collection of projects, founded in 1997 to investigate internet offending against children. Their research was focused on the establishment of a database of CSA images for victim identification purposes, and an attempt to provide a typology of CSA images found on the internet (Quayle, 2008) (Table 1-1).

Table 1-1 The COPINE scale (Merdian *et al*., 2013; Quayle, 2008).

Level of indecency		Details
1	Indicative	Non-erotic, non-sexualised pictures of children in underwear from commercial sources or family pictures. Context and organisation by the collector indicates inappropriateness.
2	Nudist	Naked or semi-naked children in appropriate nudist settings and from legitimate sources.
3	Erotica	Surreptitiously taken photographs of children in play areas or other safe environments, showing underwear or varying degrees of nakedness.
4	Posing	Deliberately posed pictures of fully or partially clothed children where amount, context and organisation suggest sexual interest
5	Erotic posing	Deliberately posed photographs in sexualised or provocative poses.
6	Explicit erotic posing	Photographs of children with emphasis on genital areas, either fully or partially clothed.
7	Explicit sexual activity	Photographs of children touching, mutual or self-masturbating, oral sex and intercourse by a child, no adult involved.
8	Assault	Photographs showing children as subject of sexual assault, including digital touching, involving an adult.
9	Gross assault	Grossly obscene pictures of sexual assault, involving penetrative sex, masturbation or oral sex, involving an adult.
10	Sadistic/Bestiality	Photographs showing a child bound, beaten, whipped or other pain implied, or an animal involved in sexual relation.

The COPINE scale was produced as an indicator of how children are victimised through CSA related crimes, and has now been integrated into the Interpol Child Abuse Image Database (Beech *et al*., 2008; Merdian *et al*., 2013). It has also been adopted by the courts as a measure of the seriousness of the offence and to inform legal decisions about crimes relating to CSA (Quayle, 2008). Guidelines, based on the COPINE scale, were produced by the Sentencing Advisory Panel as indication of factors that should be taken into consideration when deciding the correct level of sentence in such crimes (Sheldon and Howitt, 2007). For this purpose, the 10-point COPINE scale was adapted to a 5 point sentencing structure (Merdian *et al*., 2013) (Table 1-2).

Table 1-2 Five point scale used to categorise indecent images of children (pre 2014) (Bryan, 2014)

Level of indecency	**Details**
1	Images depicting erotic posing with no sexual activity
2	Non-penetrative sexual activity between children, or solo masturbation by a child
3	Non-penetrative sexual activity between adults and children
4	Penetrative sexual activity involving children or both children and adults
5	Sadism or penetration of, or by, an animal

This 5 point scale has recently been replaced with the publication of new guidelines in 2013, that were to be applied, after 1st April 2014, to all sexually related offences (Table 1-3).

Table 1-3 Three point scale used to categorise indecent images of children (Bryan, 2014)

Image category	**Details**
Category A	Images involving penetrative sexual activity and images involving sexual activity with an animal or sadism
Category B	Images involving non-penetrative sexual activity (NB: no distinction between non-penetrative sexual activity between children and between children and adults)
Category C	Indecent images not falling within A or B.

Further to the re-categorisation of image content, the new guidelines differentiate between the roles of the offender: possession, distribution (possession with a view to distributing or sharing images) and production (taking or making of any image at source). Having these three categories and three roles allows for a 9 point sentencing structure (Sentencing Council, 2013) (Table 1-4).

Table 1-4 Nine point scale used to determine the appropriate sentence for offences relating to indecent images of children; based on the 3 point categorisation of images and the 3 defined roles of the offender (Sentencing Guidelines Council, 2003)

	Possession	**Distribution**	**Production**
Category A	26 weeks' – 3 years' custody	2 – 5 years' custody	4 – 9 years' custody
Category B	High level community order – 18 months' custody	26 weeks' – 2 years' custody	1 – 4 years' custody
Category C	Medium level community order – 26 weeks' custody	High level community order – 26 weeks' custody	1 – 3 years' custody

In the U.K. the legal minimum age whereby an individual can consent to sexual intercourse is 16 years of age, therefore, any sexual activity occurring below this age, is deemed sexual abuse. The investigation of such crimes can be challenging, as acquiring reliable testimonies from young children can be impossible or extremely difficult (Ferguson and Raitt, 2013).

The comparison of similarities and differences between digital images based on anatomical features has therefore provided powerful evidential statements in cases where physical evidence is often lacking (Ferguson and Raitt, 2013). To date, this approach has led to a change of plea in over 80% of cases (S. Black, 2015, personal communication, 27 January). Despite this success of the current method the discipline of forensic science as a whole is under a great deal of pressure to validate their practices, methods and reporting to meet the demands of the court room; an issue which will be discussed in more detail in section 4.7.

Therefore the foundation of this research is to address the issue of validity regarding the assessment of anatomical features in the hand, when used as evidence to discriminate between two individuals. Furthermore, to ensure the methods employed in this process have the appropriate statistical support, to ensure the continued viability of this method of identification.

1.2 Outline of the thesis

This thesis will begin by examining the current relevant literature to establish how best to develop the approach of using anatomical features as an aid to identification. To explore this, literature relating to the anatomy of features including superficial vein patterns and surface features was examined. With both of these areas of anatomy being of growing interest to the biometrics industry, literature relating to the biometric industry was also studied, whilst remaining true to the current developments and changes in forensic practice and legal admissibility requirements.

Results from the current research will start by addressing the variability of vein patterns and anatomical surface features in the hand, in relation to the use of these features as a tool for human identification in forensic investigations.

All research was conducted with a view to increasing the probative value of utilising anatomical indicators of identity for the comparison between two image sets, in relation to the current legal and admissibility requirements.

This research will also address issues pertaining to image quality in forensic situations to establish if information is lost between a typical forensic case image seized from a suspect's personal device and the type of images which are taken of the suspect in police custody; and if so, how much information is lost.

The results pertaining to each of the groups of anatomical features (superficial vein patterns and anatomical surface features) will be presented in independent chapters

(chapters 6 and 7) due to the differing methods of analyses required for each dataset. The third chapter of results presents the two feature groups considered together (chapter 8).

The concluding chapter relates all findings to their forensic application, and how this research has added to the current relevant literature. The strengths and weaknesses of each study will be discussed before recommendations for future study are outlined with a view to showing the longevity and applicability of the methodologies presented in this thesis.

2 AIMS AND OBJECTIVES

The overall aim of the project was to develop an existing methodology concerned with establishing similarities and differences between two sets of images, specifically from anatomical information seen on the dorsum of the hand. This would comprise the establishment of a large database of hand images upon which empirical research could be conducted through the introduction of network analysis for quantification purposes, to establish the extent to which the features on the dorsum of the hand vary in both standardised and non-standardised conditions.

This involved two sets of information (superficial vein patterns and anatomical surface features); gathered in different ways, with the ultimate aim to combine all information to establish the discriminatory power of considering multiple features.

For both the anatomical surface features and the vein patterns, the central aims were the same; to establish the discriminatory capabilities of the features in terms of identification and the validity and robusticity of the technique used to extract the relevant information from digital images.

These central aims can be summarised in five points:

1) To determine how reliable and repeatable is the method of extracting vein patterns/ surface feature information for the purposes of subsequent analysis [intra and inter-observer studies].
2) To determine to what extent the components of a vein pattern and the surface features vary across the sample population.
3) To investigate the influence of biological characteristics on vein pattern and surface feature variation.
4) To investigate how robust the vein pattern /surface features are when assessed in an image of poor quality; representing a likely forensic case image, compared to a standardised image; representing a suspect image taken in custody.
5) To establish how information from both feature groups can be combined and establish whether this increases the variability of using features on the dorsum of the hand for identification purposes.

3 HYPOTHESIS

It is hypothesised that the method for extracting and recording vein patterns and surface feature information will be repeatable when performed by a single observer; however differences may occur when the method is performed by observers of varying knowledge and experiences.

It is hypothesised that the vein pattern features and surface features will vary to the extent that no two individuals within the database will possess the same combination of features, and that used together, will be more discriminative than when used alone.

Finally, it is hypothesised that both vein pattern and surface features information will be more visible in the standardised conditions, compared to the ‘forensic case type’ images.

4 REVIEW OF LITERATURE

4.1 Anatomy of the region of interest

Vein patterns as a discriminatory feature are well established within the biometric arena They have been proven to be successful in this role due to variability in the patterns created by the veins, thus providing discriminatory capabilities (Hartung *et al.*, 2011; Luo *et al.*, 2010; Prathyusha and Kumar, 2009; Wang *et al.*, 2008).

In an attempt to understand this variation for the purposes of this research, the anatomy and embryological development of the vein patterns will be examined. In particular, this section considers the anatomy related to the region of interest concerned in this research; the dorsum of the hand. This section will describe the anatomy and embryological development in this region as well as a description of the superficial veins. The section will then go on to describe a selection of anatomical and acquired surface features that are often observed on the dorsum of the hand and are therefore utilised in the investigation of suspect identification or exclusion in forensic investigations.

This will lead on to an introduction to biometrics and how vein patterns and surface features are utilised to establish identity though the use of commercial products.

4.1.1 Development of the upper limb

The limbs develop from limb buds; small bulges on the ventro-lateral wall of the developing embryo, in a relatively small window of the gestational period; 4 to 8 weeks (Larsen, 1993; Moore *et al.*, 2013; Scheuer and Black, 2000). The limb buds elongate by proliferation of the mesenchyme (Moore *et al.*, 2013), until eventually, the distal free ends of the limb buds form into flattened paddle-like hand plates. Within these plates, digital rays form by the end of 6th week, which outline the pattern of the digits of the hand. Loose mesenchyme between the rays breaks down by apoptosis, gradually separating the rays from one another to create digital notches; the primordial digits of the hand (Figure 3.1) (Larsen, 1993; Moore *et al.*, 2013; Sadler, 2012; Scheuer and Black, 2000).

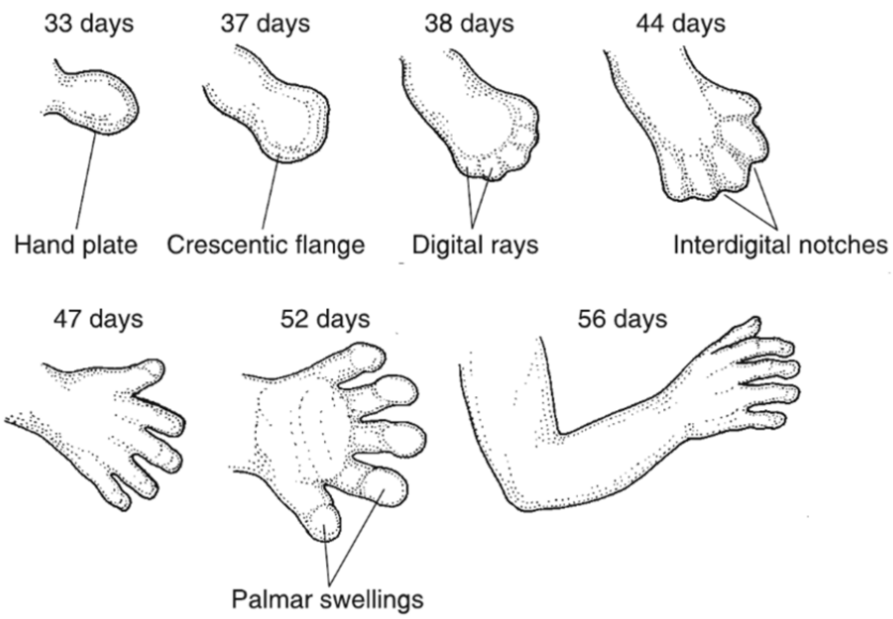


Figure 3.1 Development of the hand from day 33 - 56. (Scheuer and Black (2000) Development of the upper limb between 5 and 8 embryonic weeks. Fig 9.26, p 321).

In the 7th week of gestation the upper limb rotates so that the palm faces caudally and medially, and the limb has undergone horizontal flexion so that it lies in the parasagittal plane (Larsen, 1993; Sadler, 2012; Scheuer and Black, 2000) and the thumbs lie laterally (Sadler, 2012).

By the end of this period, the upper limb represents the more adult-like structure regarding position and the defined digits.

4.1.2 Development of the vasculature

The vasculature begins to develop early in the third week of gestation (Larsen, 1993). By this time, endothelial cells have differentiated into angioblasts, described as pre-vascular endothelial cells (Eichmann *et al.*, 2005, Tomanek, 2002).

The vasculature forms in two ways; vasculogenesis, where vessels arise from blood islands, and angiogenesis, which involves the sprouting of new vessels from pre-existing stalks. Vasculogenesis begins around day 18 with the formation of blood islands in the extra-embryonic mesoderm (mesoderm of the yolk sac) from aggregations of angioblasts (Eichmann *et al.*, 2005; Flamme *et al.*, 1997; Larsen, 1993; Tomanek, 2002; Risau, 1999; Sadler, 2012). The blood islands anastomose to form a meshwork of capillaries which acts as a scaffold for the preliminary circulation (Eichmann *et al.*, 2005; Larsen, 1993; Sadler, 2012) (Figure 3.2).

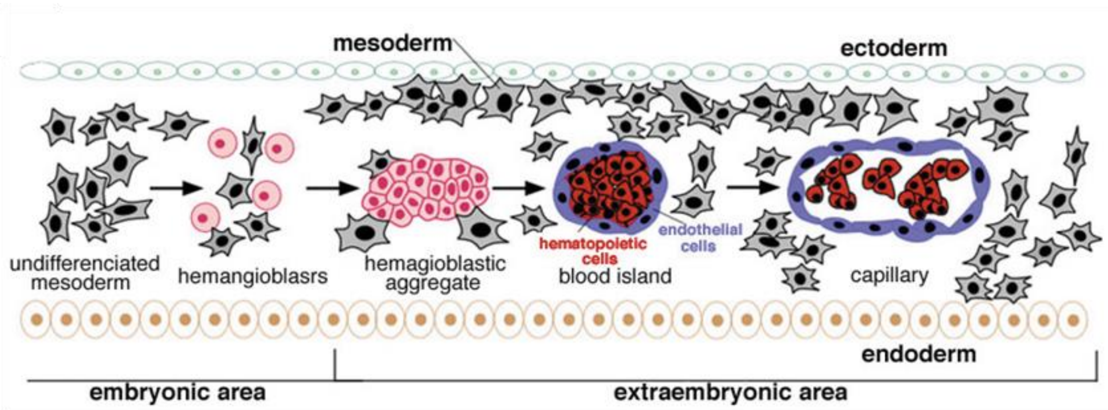


Figure 3.2 Embryonic development of blood vessels (Eichmann *et al*., 2005).

This capillary network is already formed before the onset of the first heartbeat, suggesting that early development of vasculature is independent of perfusion and metabolic stress, contrary to the later development and maintenance of blood vessels. After onset of the heartbeat, the extra-embryonic plexus is remodelled and expanded into a mature network of arteries and veins by angiogenesis (Tomanek, 2002). Hemodynamic forces generated by the heart are thought to be one of the most important factors that underlie the initiation of angiogenesis and the appropriate morphogenesis of the entire vasculature (Tomanek, 2002).

In addition to these forces, it is thought that vascular growth is tightly regulated by a complex pathway of angiogenic stimulators and inhibitors as well as metabolic stress (low pH or hypoglycaemia), mechanical stress (pressure from other proliferating cells) and immune responses; however it remains unresolved how the genetic and environmental factors that influence angiogenesis interact (Tomanek, 2002).

The differentiation of the endothelial cells into arteries and veins is thought to occur due to the influence of haemodynamic forces (Moyon *et al.*, 2001) and several signalling molecules including; ephrin-B2 and members of the notch pathway (Adams, 2000; Eichmann *et al.*, 2005). Due to the involvement of these signalling pathways, it has been argued that arterial-venous differentiation is partially determined by genetics (Wang *et al.*, 1998).

It was widely held that differences in the phenotype of arterial and venous endothelial cells were attributable to environmental factors including; hemodynamic forces, blood flow direction, oxygen levels, and interactions with smooth muscle cells. However, this was challenged with the discovery of molecules, specifically expressed on arterial or venous endothelial cells, in early development, before the onset of circulation. It is therefore thought that arterial-venous identity may be attributed on a more molecular basis, rather than environmental (Minami and Aird, 2003).

Regarding the determination of the location of the vessels, Mukouyama *et al.* (2002) found that there was a relationship between the pattern of nerves and arteries, but no association between nerves and veins was observed.

Development of the vasculature in the upper limb

The primordial cardiovascular system arises from the aortic arches, which form between day 22 and 24 during the process of embryonic folding. The first pair of arches lies in the mesenchyme of the pharyngeal arches on either side of the developing pharynx. Between days 26 and 29 arches two, three, four and six develop by vasculogenesis and angiogenesis within the respective pharyngeal arch (Larsen, 1993). The fourth and sixth aortic arches remodel to supply the upper extremities, which give rise to the subclavian, axillary, brachial and the anterior interosseous artery. In the hand, a small portion of the axial artery persists as the deep palmar arch (Larsen, 1993) (Figure 3.3).

The primitive venous system has three components; the cardinal system, viteline vein and the umbilical veins, which are visible in the fifth week of development (Sadler, 2012).The cardinal system is responsible for draining the head, neck, body wall and limbs. The original structure exists as the paired posterior (inferior) and anterior (superior) veins. These join near the primordial heart to form the common cardinal vein (Larsen, 1993).

The subclavian vein coalesces from the venous plexus on the upper limb bud and empties into the anterior cardinal vein. The brachiocephalic vein drains blood of the upper limb and the head (Larsen, 1993).

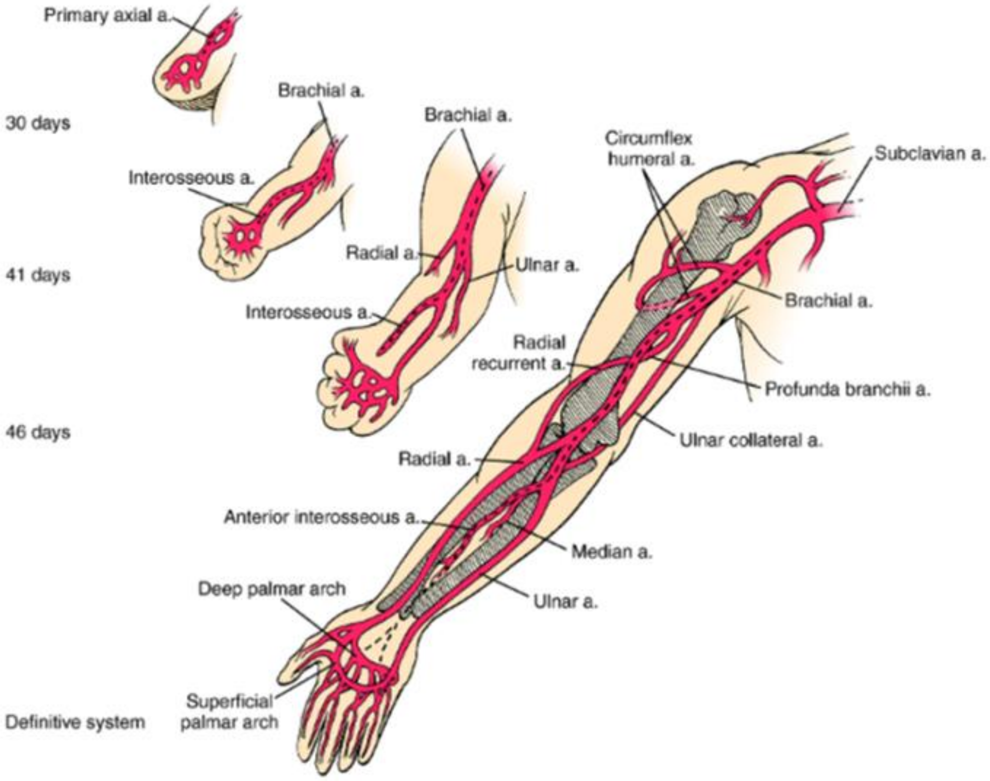


Figure 3.3 Development of the arterial system of the upper limb, Larsen (1993) Fig 8 – 9, p 183.

The literature does not extend to the development of the veins into the hand, other than what has been described. The absence of literature leaves a gap in the knowledge for understanding the regulation of vascular patterning in this region.

4.1.3 Anatomy of the adult hand

The muscles on the dorsum of the hand consist of the dorsal interossei, which are found between adjacent metacarpals. Each muscle inserts into the base of the proximal phalanx and into the extensor hood of its related digit. The first dorsal interossei is the largest and inserts into the lateral side of the index finger. This is palpable between the thumb and index finger (Drake *et al.*, 2005) (Figure 3.4).

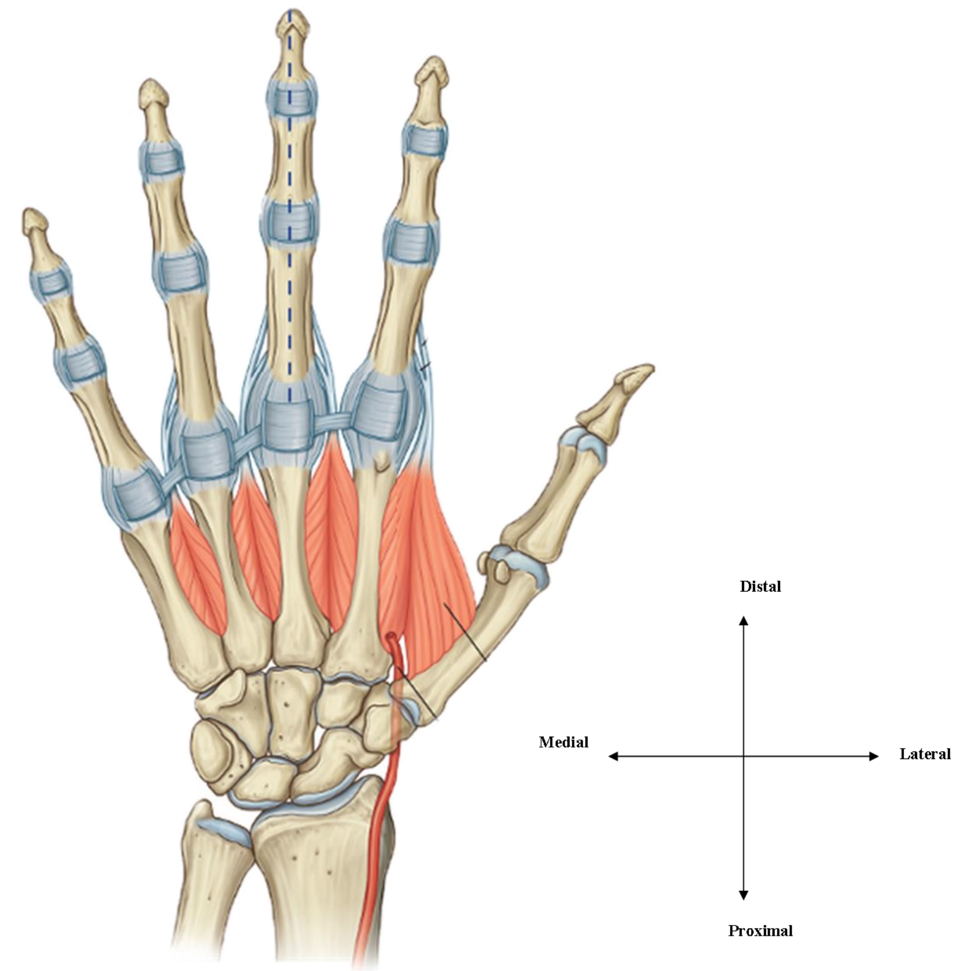


Figure 3.4 Muscles of the dorsum of the hand. Image adapted from Drake *et al.* (2005), p 718, fig 7.99.

The dorsal digital veins arise along the side of the digits (Gray, 1918) and communicate, through a series of arches between the palmar and dorsal aspect of the digits (Bergan, 2007; Doyle and Botte, 2003) before finally uniting at the proximal ends of the digits (Cunningham and Robinson, 1918) at the metacarpal-phalangeal joint (Doyle and Botte, 2003). At this union, the dorsal metacarpal veins are formed (Cunningham and Robinson, 1918, Gray, 1918, Bergan, 2007). They terminate distal to the middle of the dorsum of the hand as the 'dorsal venous arch' (Cunningham and Robinson, 1918) or 'dorsal venous network' (DVN) (Gray, 1918, Bergan, 2007).

Across the literature there are numerous descriptions of the distribution of the superficial veins in this region, as seen in Figure 3.5; few of which agree on a detailed description of the exact location of the superficial veins; likely because they are so variable.

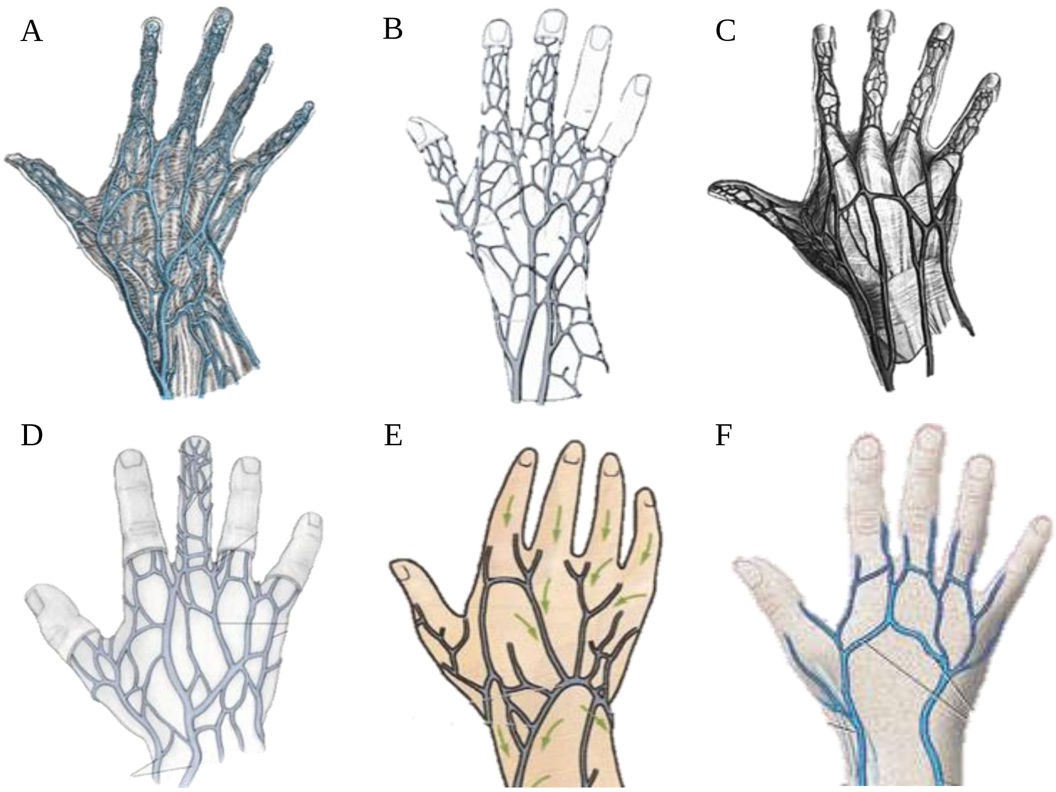


Figure 3.5 Variation in the depiction of superficial veins on the dorsal aspect of the hand: a) Gray (1918), b) Cunningham and Robinson (1918), c) Schmidt and Lanz (2003), d) Doyle and Botte (2003) , e) Moore and Agur (2007), f) Drake *et al.* (2010)**.**

From the DVN arise the superficial veins of the forearm, the cephalic and basilic veins (Doyle and Botte, 2003, Moore and Agur, 2007). The cephalic vein proceeds laterally over the anatomical snuffbox (Drake *et al.*, 2005) and the basilic medially (Bergan, 2007; Cunningham and Robinson, 1918; Drake *et al.*, 2010; Gray, 1918; Moore and Agur, 2007).

4.1.4 Anatomy of surface features on the dorsum of the hand

In addition to the superficial vein patterns on the dorsum of the hand, anatomical or acquired features on the skins surface on the dorsum of the hand are also utilised in the investigation of crimes, when this region of anatomy is depicted within a digital image. The use of these features is predicated on the underlying anatomy and physiology of these features which will now be explained.

Pigmentation

Pigmentation in the skin is largely determined by the presence of pigment producing cells, melanocytes. Melanin within these cells is the main contributor to pigmentation, along with carotenoids and haemoglobin (Lin and Fisher, 2007).

Hyperpigmentation refers to an area of increased colour compared to the surrounding skin. This occurs due to deposits of melanin pigment in either the basal epidermis or dermis of the skin (Pray, 2006; Trozak, D.J., Tennenhouse, D.J., Russell, 2006). There are many types of hyperpigmentation, therefore only a selection of the most commonly found shall be described.

Ephelides

Ephelides, or more commonly known as freckles (Pray, 2006) are areas of increased pigment production seen on the surface of the skin (Bastiaens *et al.*, 2001; Trozak, D.J., Tennenhouse, D.J., Russell, 2006). They can be circumscribed, oval or irregular in shape and range from 1 mm to 3 mm in diameter. They can occur in tightly packed groups and may even become confluent (Barnhill *et al.*, 2004; Bastiaens *et al.*, 1999; Pray, 2006). Ephelides appear in early childhood and can fade, or disappear with age (Bastiaens *et al.*, 2004, 1999; Monestier *et al.*, 2006).

Studies have shown the prevalence of ephelides to range from 8.38% (Yang *et al.*, 2007) to 24.8% (Pavlotsky *et al.*, 1997).

Studies by Bastiaens and colleagues concluded that ephelides are mostly genetically determined, particularly that there is a strong association between the MC1R gene and freckling (Bastiaens *et al.*, 2004, 2001). Despite the genetic link, ephelides have also been shown to emerge in response to sun exposure (Pray, 2006; Trozak, D.J., Tennenhouse, D.J., Russell, 2006), and therefore most commonly occur on sun exposed areas of skin, and become more apparent in summer months and fade in the months where sun is limited (Bastiaens *et al.*, 2001).

Ephelides are most common in people with fair skin, red or blonde hair and blue or green eyes (Barnhill *et al.*, 2004; Bastiaens *et al.*, 1999; Pray, 2006); a demographic that is more sensitive to sun exposure. The link with fair skinned individuals and ephelides may also support the genetic link.

Lentigines

Lentigines are described as an area of increased melanocytes at the dermo-epidermal junction in the skin. There are two types of lentigines, solar and non-solar (Trozak, D.J., Tennenhouse, D.J., Russell, 2006).

Solar lentigines (SL) are often confused with ephelides due to their similarity in morphology (Bastiaens *et al.*, 1999; Rhodes *et al.*, 1991). The two features can be distinguished histologically; ephelides are hyperpigmentation of the epidermis, with an equal or reduced number of melanocytes compared to surrounding skin, but the melanocytes are more active, therefore exhibiting more concentrated pigment (Breathnach, 1957). Conversely, SL's have been described as having a higher number of melanocytes compared to surrounding areas (Andersen *et al.*, 1997; Hodgson, 1963) as cited in (Bastiaens *et al.*, 1999).

SL's have been described as light brown, dark brown, black or yellow in colour (Pray, 2006). They vary in size from 5 mm to 10 mm, but can be up to 50 mm with irregular margins; several close lentigines can join to form a larger mass (Pray, 2006).

They are not present at birth, but are acquired, usually in the second decade, except with intense sun exposure (Trozak, D.J., Tennenhouse, D.J., Russell, 2006), gradually increasing with age (Bastiaens *et al.*, 2004, 1999; Monestier *et al.*, 2006), reaching their peak in numbers around the 5^{th} decade. A study by Bastiens *et al.* (2004) showed that SL's were associated with chronic sun exposure and other signs of photo damage within the skin. As with ephelides, SL's tend to appear on exposed areas such as; the face, neck, dorsum of the hands and forearms (Pray, 2006; Trozak, D.J., Tennenhouse, D.J., Russell, 2006).

No association has been found between skin type/colour and hair colour suggesting that genetic factors play a minimal, if any role in the development of SL's (Bastiaens *et al.*, 2004).

Non-solar lentigines do not appear in response to sun exposure and do not regress with the lack of exposure, unlike SL's. They tend to be dark brown in colour, oval or round symmetrical (Trozak, D.J., Tennenhouse, D.J., Russell, 2006) and less than 5 mm in diameter.

They tend to appear within the first decade of life and remain quite stable throughout life, as they do not change in colour or size, even with sun exposure (Trozak, D.J., Tennenhouse, D.J., Russell, 2006).

Melanocytic nevi

Nevus in the broadest sense refers to an abnormality or irregularity attributed to hereditary or embryonic development. Within dermatology the term refers to a large number of congenitally acquired hematomas, usually in reference to ‘benign neoplasms’ composed of pigment cells. (Trozak, D.J., Tennenhouse, D.J., Russell, 2006).

Melanocytic nevi (MN) are more commonly known as moles. Some research reports that MN begin to develop early in childhood (Harrison *et al.*, 2000), however most appear during puberty and in the 2nd decade of life. Their prevalence reaches a plateau by age 15 years in males (Nicholls, 1973); after peaking they undergo gradual shrinkage and can eventually completely disappear (Stegmaier, 1959).

MN that are present from birth are called congenital nevi (also known as birthmarks). It is also possible for nevi to develop after birth; so called common acquired MN. The two are very similar in appearance and can be indistinguishable (Tannous *et al.*, 2005).

The appearance of MN’s can change throughout life; mostly, they have a regular, smooth, well demarcated border, and are round or oval in shape. They can also be raised from the surface of the skin with a ‘verrucous’ or ‘nodular’ appearance (Tannous *et al.*, 2005).

Throughout their life cycle they have different structures, and therefore different terminology. Junctional nevi are pigmented macules of <5 mm, are tan to very dark brown and oval/round in shape. Some of these remain stable, while some can increase in size over time and they may become raised. They then become compound nevi; this process is benign and can continue until middle age. Compound nevi are typically round/oval shaped, with a smooth, shiny surface, tan to dark brown in colour and usually <6 mm.

Studies have shown the prevalence to be 11.8% (in a population of 17 year old Israeli males (Pavlotsky *et al.*, 1997)), or 9% (in a population of Caucasian males and females aged between 21 and 62 years (Black *et al.*, 2013b)).

The study by Black *et al.* (2013b) went on to describe that the most prevalent locations of MN were in the grid cell marked 3 and 7 in Figure 3.6.

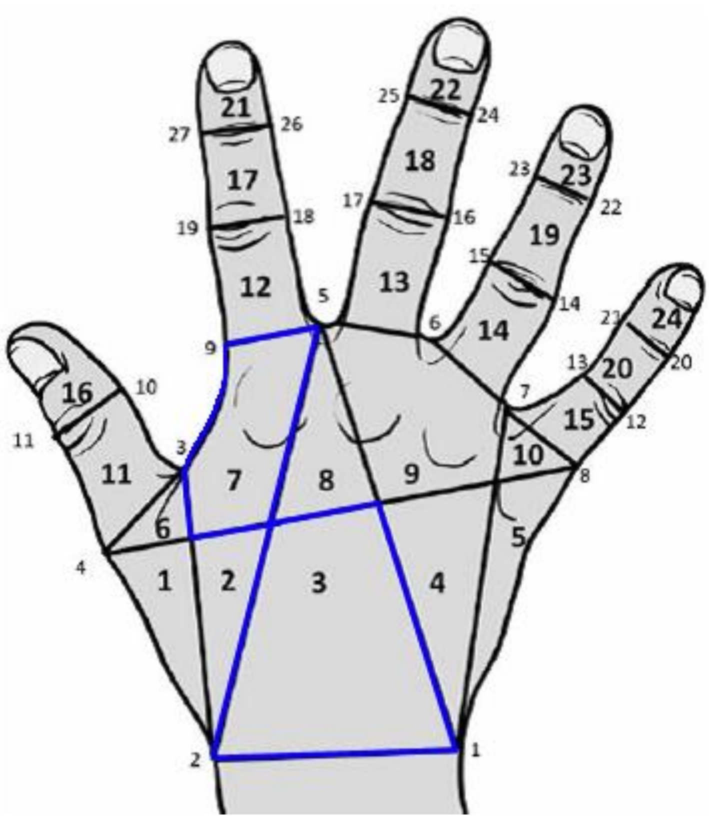


Figure 3.6 Most prevalent locations of MN (Black *et al.*, 2013b)

Scarring

The hand is generally exposed to the individual's external environment in daily tasks and interaction (Napier, 1993). Due to this level of exposure compared to other regions of the body, the hand is often prone to injury (Lloyd, 1985; Rosberg and Dahlin, 2004).

Males between the ages of 12 and 29 are the most likely to incur an injury to the hand (Clark *et al.*, 1985; Hill *et al.*, 1998).

Specifically investigating the incidence and location of scars on the dorsum of the hand, Black *et al.* (2013) found that for males, an average of 1.42 and 1.97 scars were located on the right and left hands respectively. 49% of the male right and 40% of the male left hands showed no scarring, and 25% of the male sample had no scarring on both hands. They found that from the male sample, scars were more common in the right hands than in the left hands (p = <0.001). With regards to location, it was seen that scars were most likely to be found in the index and middle finger corridors (sections 21, 17, 12, 7 and 22, 18, 13 9), which can be seen in Figure 3.6 (Black *et al.*, 2013a). Other researchers have found that scars were most commonly found at the lateral and medial borders of the hands (Hill *et al.*, 1998; Rosberg and Dahlin, 2004), with Hill *et al.* (1998) reporting that 17% of injuries where in the thumb region, 13% on the index finger, whilst the dorsal surface of the hand reporting only 3% of the injuries.

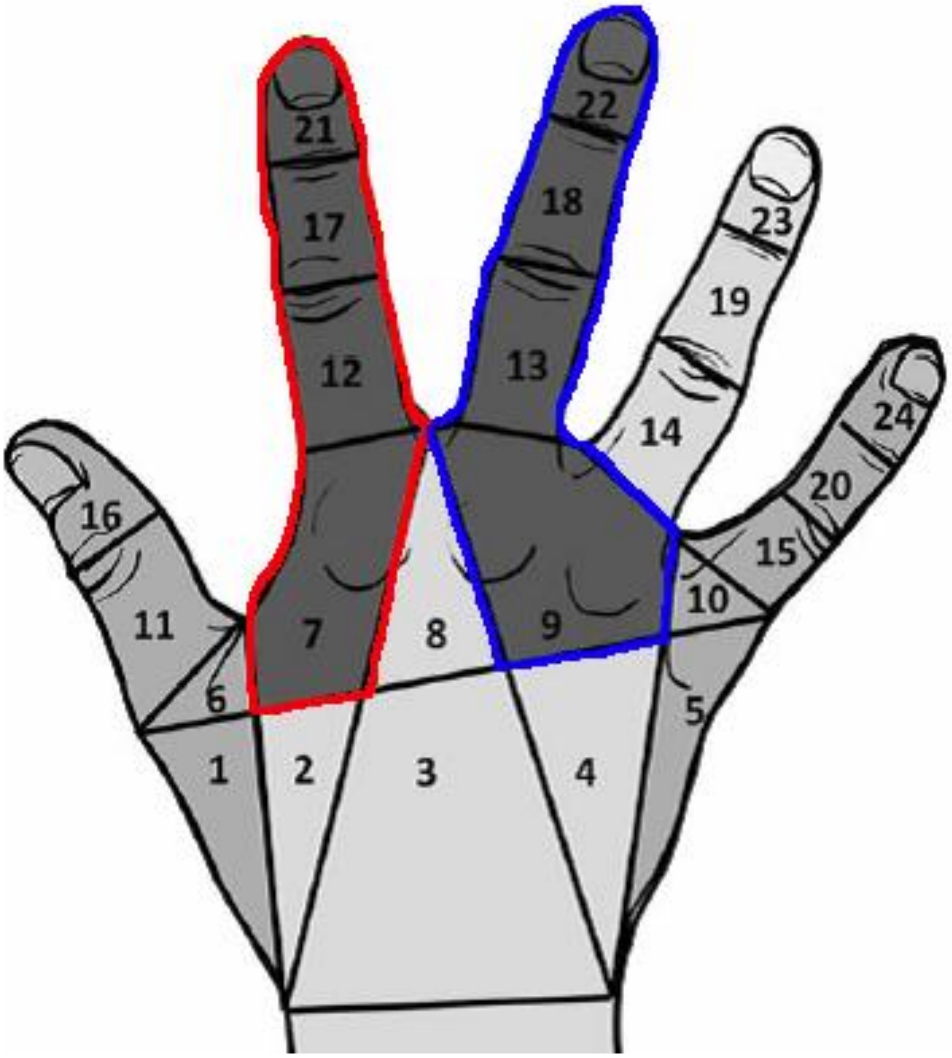


Figure 3.7 Regions of the hand where scars were most predominantly identified. (Black *et al.*, 2013); adapted to highlight the middle (blue) and index (red) corridors.

Hair

Hair is a relevant feature to discuss, not for its discriminatory capability, but as it has been attributed to concealing underlying anatomical information, such as vein patterns, thus reducing the level of detail available (Khan and Khan, 2009; Lingyu and Leedham, 2006; Paquit *et al*., 2007).

Hair is a universal trait, and is present across the body with the exception of the soles of the feet and palms of the hands (Szabo, 1967). On the dorsum of the hand, hair coverage has been reported to be thicker along the border of the hypothenar eminence whereas the thumb region is usually free of prominent terminal hairs. Schmidt and Lanz (2003) state that occasionally hair 'whorls' are present over the region of the anatomical snuffbox (Figure 3.8). Setty (1964) described the distribution of hair on the dorsum of the hand as either covering a large part of the dorsum of the hand, restricted to the medial and lateral borders, or restricted to the medial border.

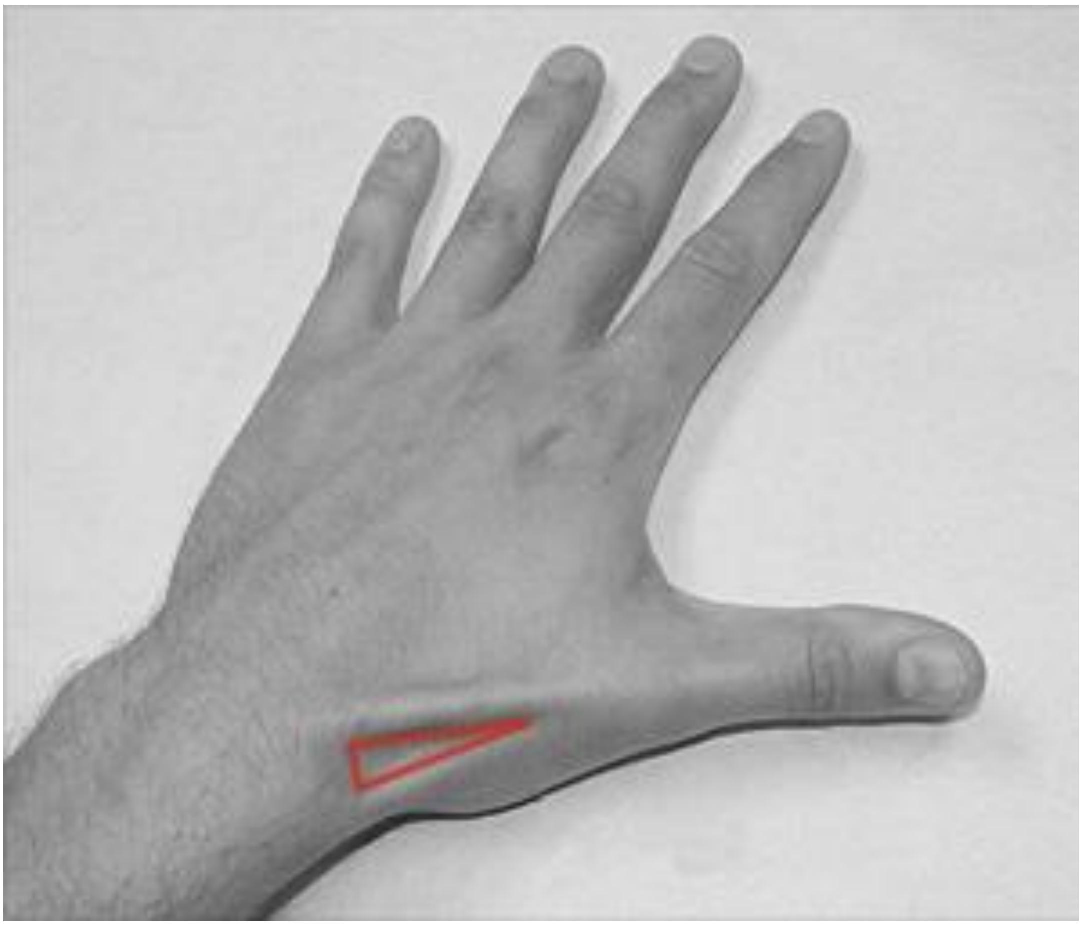


Figure 3.8 Location of the anatomical snuffbox depicted by the red lines (Jones, 2014).

The features described have been utilised in forensic investigations (with the exception of hair). Superficial vein patterns and pigmentation have been shown to have molecular, genetic and environmental underpinning, with scars being purely incidental. This range of aetiologies underpinning the different features used to establish identities, enhances their discriminatory capacity, by indicating that the features are entirely independent, and therefore combinations of these features is thought to be highly discriminatory.

4.2 Introduction to biometrics

The word ‘biometric’ literally means, ‘life measurements’ and is derived from the Greek words ‘bio’ (life) and ‘metrics’ (to measure) (Mayhew, 2015). Biometrics are based on the principle of using personal attributes to discriminate between individuals for the purposes of personal identification, verification or authentication (Desmarais, 2000). These attributes are measurable, biological or behavioural characteristics that can be used for automated detection (Goudelis *et al.*, 2008; Lee *et al.*, 2011). Firstly, it is important to clarify the terms, ‘identification’ and ‘authentication’.

The term identification refers to a scenario where a person compares a set of previously recorded identifiers, with another set of identifiers and establishes whether they comprise the same set of information. Authentication on the other hand, firstly requires an individual to be identified; this identity must then be verified against something that confirms this individual possesses the identity they have claimed (Harper, 2006).

To contextualise these terms, consider the example of logging into your email account; entering your email address identifies you to the system, entering your correct password authenticates you (Harper, 2006).

Personal identification can be defined by one of three levels of authentication (The Biometric Consortium, 2006):

1. Something you **have**; key, swipe card or passport.
2. Something you **know**; password, PIN or a unique memory.
3. Something you **are**; biometrics, behavioural or biological

Personal identification methods categorised as ‘something you have’ and ‘something you know’ are met with challenges; personal identification numbers (PIN’s) and passwords may be forgotten or stolen, and cards or keys may be lost, stolen or copied (Desmarais, 2000). For these reasons, biometrics have attracted attention in recent years from industry and research communities due to their enhanced security benefits in comparison to traditional methods of personal identification (Desmarais, 2000; Goudelis *et al.*, 2008; Miura *et al.*, 2004).

The ‘something you are’ methods are also known as ‘biometrics’. Biological features such as fingerprints, hand geometry, iris and vein pattern recognition among others have been used as biometric modalities. Behavioural characteristics are said to be less robust than biological characteristics as they are more open to fraud. They include; voice verification, signature or keystroke dynamics and gait (Desmarais, 2000; The Biometric Consortium, 2006; Wilson, 2010).

Biometric modalities must be selected carefully, and the operational systems rigorously tested to fulfil certain criteria to ensure they are robust. A biometric must fulfil four key criteria:

- Universality; everyone (or the majority of the population) possesses the characteristic.
- Distinctiveness; the differences between two individuals should be sufficient to be discriminatory.
- Permanence; will not change over time and cannot be altered.
- Mining and measurement: Relatively easy to collect and quantify.

(Burghardt, 2009; Jain *et al.*, 2004b; The Biometric Consortium, 2006)

Biometrics have a range of uses in a variety of sectors in society and can be categorised into three main areas; commercial, security and forensic (Jain *et al.*, 2004a, 2004b).

An example of commercial use of biometrics is utilising vein patterns to make a payment, instead of presenting a bank card (Lund University, 2014); a technology that has seen a recent surge of interest, development and integration in society (Ahmed, 2014; Gent, 2014; Gompertz, 2014; Kleinman, 2013; Maisto, 2014).

Governments have employed biometric systems for heightened security for purposes of controlling immigration and border access control (Lee *et al.*, 2011; Schulman, 2002). The ‘Border Crossing Card program’ between the United States and Mexico requires frequent travellers to hold a biometric enhanced identification card. These cards comprise a photograph of the individual, their fingerprint and personal details embedded in digital format within the card (Schulman, 2002).

Biometrics are also used in forensic science to aid in the identification of perpetrators and victims of crime. One example is the use of facial identification from videos or images and voice verification employed by the Forensic Audio, Video and Image Analysis Unit (FAVIAU) of the FBI (Spaun and Bruegge, 2008).

Reliability of biometric systems

It has yet to be determined with certainty whether any biometric modality can be described as 'unique' (Cross and Smith, 1995). Instead, to test the viability of the recognition system, performance indicators are used to assess the reliability and error rate of the system.

This can be measured by the calculation of the false rejection rate (FRR) and false acceptance rate (FAR), and the inverse relationship of the two (O'Connor, 2002). The FRR (or the false non-match rate, FNMR) is the probability that a biometric system will fail to identify an individual already enrolled on the database, or the probability it will fail to verify an individual based on a legitimate claim (Fujitsu Limited, 2013; Jain *et al*., 2004b; Luo *et al*., 2010; Wilson, 2010). The FAR (or false match rate, FMR) (Luo *et al.*, 2010) refers to the probability that a biometric system will incorrectly verify an individual's identity (Fujitsu Limited, 2013; Jain *et al.*, 2004b; Luo *et al.*, 2010) by failing to identify an imposter (Wilson, 2010). Finally, the equal error rate (EER) is the rate at which the acceptance and rejection rates are equal. Therefore a low value of this, indicates a reliable system (Jain *et al.*, 1999).

4.2.1 Vein pattern biometrics

The extent of variation of superficial vein patterns has been exploited by the biometric industry, however due to biometric research largely being conducted or funded by commercial companies; the extent of variation has not been explicitly reported.

Vein pattern biometrics have been employed in several regions of the body utilising the superficial veins that reside close to the skin, including several areas of the hand; fingertip, palm and dorsum of the hand or areas where the vein pattern lies deeper, but can be extracted with specialised imaging equipment, such as the retinas.

Interest has been growing with regards to vein pattern recognition techniques as a biometric modality from industry and research communities in recent years (Wang *et al.*, 2008), as they are highly regarded for their distinctiveness, their stability over time, ease of which they can be acquired, and resistance to forgery (Hartung *et al.*, 2011; Luo *et al.*, 2010; Prathyusha and Kumar, 2009; Wang *et al.*, 2008).

Quantitative analysis of the vein pattern for identification purposes emerged from the biometric industry using infra-red (IR) image capture (Aboalsamh, 2011; Luo *et al.*, 2010). Finger vein systems have been shown to have high accuracy rates, that exceed those of fingerprints (Aboalsamh, 2011). This, along with their usability, small, contactless readers and related practicality and hygiene issues has led them to be favoured in the biometrics industry (Luo *et al.*, 2010, Hartung *et al.*, 2011, Aboalsamh, 2011).

Xueyan and Shuxu (2008) state that the use of superficial vein patterns as a biometric modality were first proposed in 1992. In 2007, vein recognition comprised 3% of the biometric market. Since then it has gained interest both from research communities and the commercial sector.

Commercially, vein patterns recognition systems have been developed by Fujitsu and Hitachi in their palm vein and finger vein products respectively (Luo *et al.*, 2010); Fujitsu have developed the PalmSecure™ technology that authenticates individuals based on their vein pattern. Fujitsu claim that palm vein biometric technology is the most accurate and practical in comparison to other popular methods (Figure 3.9) stating the benefits to include; the hygiene of contactless system, resistance to fraud (as the veins reside beneath the skin) and finally high performance rates as summarised in Table 3-1.

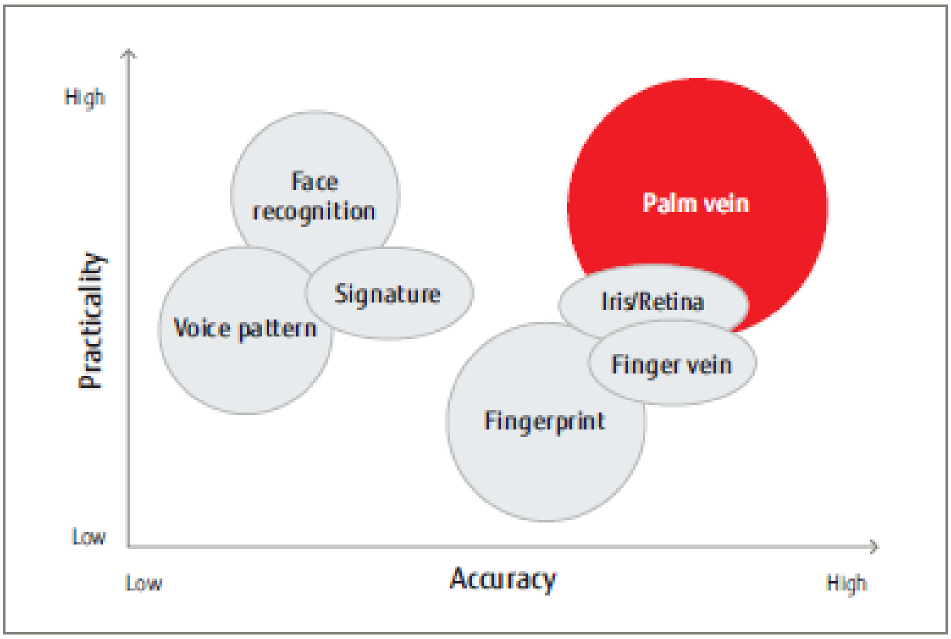


Figure 3.9 The benefits of vein biometrics in terms of accuracy and practicality, in relation to other popular biometrics (Fujitsu Limited, 2013).

Table 3-1 Table showing performance rates of popular biometric systems (Fujitsu Limited, 2013).

False Acception Rate (FAR) and
False Rejection Rate Comparison (FRR)

Authentication method	FAR (%)	If FRR (%)
Face recognition	≈ 1.3	≈ 2.6
Voice pattern	≈ 0.01	≈ 0.3
Fingerprint	≈ 0.001	≈ 0.1
Finger vein	≈ 0.0001	≈ 0.01
Iris/Retina	≈ 0.0001	≈ 0.01
Fujitsu Palm vein	< 0.00008	≈ 0.01

Furthermore, the PalmSecure™ sensor and its algorithm have been approved by the International Organisation for Standardisation (ISO) common criteria certification for security (Fujitsu Limited, 2013); which is the basis for the government driven certification scheme to provide assurance that the technology, implementation and evaluation of a computer security product has been tested in a rigorous manner and shown to be repeatable (Fujitsu Limited, 2013).

Technologies involving vein pattern recognition are, or have the potential to be, used in a range of industries which are summarised in Table 3-2.

Table 3-2 Summary of the uses for vein pattern recognition systems. (Croma Biometrics, n.d.; Croma Security Solutions, 2013; Fujitsu Limited, 2013; Gent, 2014; Jonas *et al.*, 2014; Maisto, 2014; Police Oracle, 2012; Vrankulj, 2014).

Industry	**Purpose**
Retail	Cashless payments
Financial	ATM access
Security	Personal ID, social insurance, physical access control in HM prisons and immigration removal centres
Healthcare	Patient registration/identification
Automotive	Attendance tracking, access management
Entertainment	Access to leisure facilities
Education	Access control to secure campuses or buildings

Many of the techniques for vein pattern recognition are based on existing methods used in the fingerprint examination; through similarities in the components of the pattern. In the U.K. a 16-point standard for fingerprint identification was employed since 1924, as recommended by New Scotland Yard. This was on the premise that 16 points of similarity were required between two fingerprints for identifications to be taken to court (Campbell, 2011). The 16 points related to features, or minutiae including bifurcations (point at which a ride of the print splits into two), a dot (an isolated section of ridge) and ridge endings (U.S. Department of Commerce, 2012). In 2001 (England and Wales) and 2006 (Scotland), the 16 point scale was abandoned, in favour of a 'non-numeric standard'. Furthermore, it was recommended by the Fingerprint Inquiry that fingerprint evidence be recognised as opinion evidence rather than fact, as fingerprint identification techniques involved a series of subjective judgements (Campbell, 2011).

How do vein pattern recognition systems work?

Vein pattern recognition systems follow the same general approach as most biometric systems, which consists of a four part protocol; enrolment, authentication, identification and decision (Luo *et al.*, 2010) (Figure 3.10).

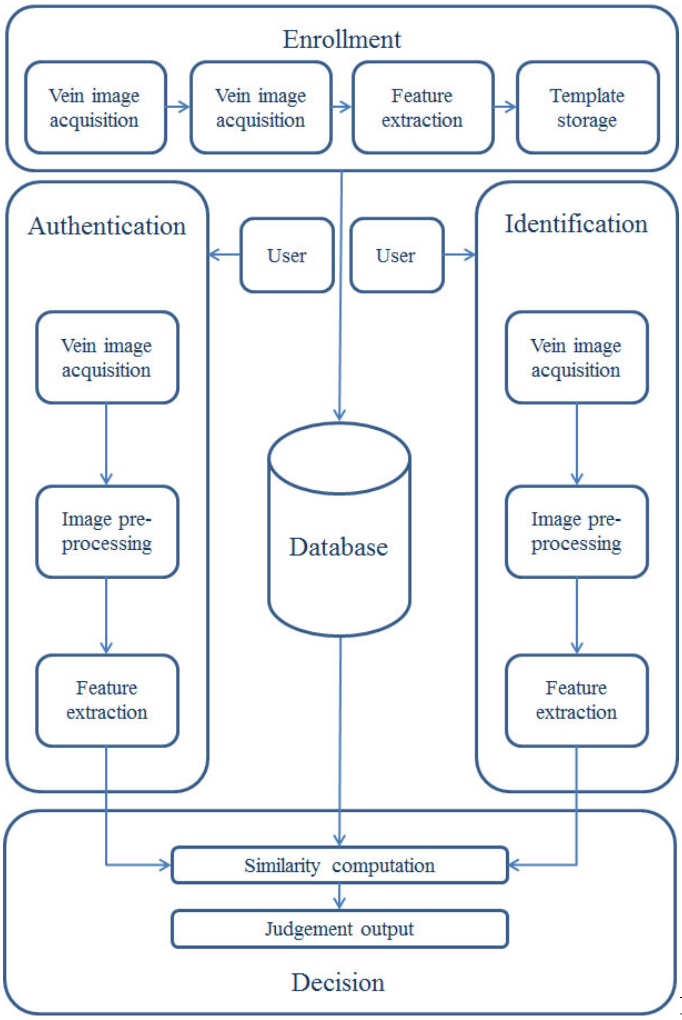


Figure 3.10 Framework of vein pattern recognition system (Luo *et al.*, 2010) adapted by Meadows (2011).

Enrolment

The enrolment stage involves capturing the biometric feature using a sensor; such as an infra-red scanner to capture an image of superficial veins beneath the skin. Relevant pattern information is extracted from the images and then stored on the intrinsic database of the biometric system. This stored information constitutes the template used as a reference in later stages (Luo *et al.*, 2010).

Vein image acquisition

In visible light and to the naked eye, the superficial vein pattern is not easily discernible due to the fact that they reside beneath the skin, and other anatomical surface features obscuring the vein pattern such as; moles, scars, pigmentation, hair, level of subcutaneous fat and hand position among other factors (Aboalsamh, 2011; Cross and Smith, 1995; Lee, 2012). For this reason, many vein pattern systems have adopted the use of near infrared (NIR) and far-infrared (FIR) imaging to obtain an image of higher contrast and reduced noise.

When NIR is directed onto the skin, generated from light emitting diodes (LED's) (Aboalsamh, 2011), it is absorbed by the deoxygenated haemoglobin in venous blood (Luo *et al.*, 2010, Miura *et al.*, 2004, Hartung *et al.*, 2011, Prathyusha and Kumar, 2009) more than surrounding tissues (Cross and Smith, 1995). A NIR sensitive closed circuit device camera captures a digital image, which results in an image where the vein patterns can be readily observed as dark lines on a pale background (Luo *et al.*, 2010, Aboalsamh, 2011, Miura *et al.*, 2004, Wang *et al.*, 2008, Lingyu and Leedham, 2006) (Figure 3.11) .

FIR imaging can also be used for vein pattern recognition systems. FIR imaging uses the heat emitted from blood vessels, and measures the temperature gradient between the superficial veins and surrounding tissues (Cross and Smith, 1995; Lingyu and Leedham, 2006) to detect their location (Hartung *et al.*, 2011).

NIR imaging is primarily used in vein pattern biometric systems as, FIR imaging, and the equipment required to perform it can be very expensive and sensitive to ambient conditions (Prathyusha and Kumar, 2009).

Image processing

Once the image is captured, it is processed by the biometric system to extract vein pattern information. This commences by normalising the image to account for adjustments in angle and location of the region of interest between users (Miura *et al.*, 2004). The image is then enhanced which usually involves contrast enhancement, noise reduction (Figure 3.11b), and the addition of edge enhancing algorithms (Hartung *et al.*, 2011). To obtain a clearly defined image of the vein pattern, the pattern must be separated from the background. This can be done using a thresholding algorithm which works by assigning threshold values to every pixel in the image. Pixels with values below a set threshold are considered to be background while pixels equal to or above the threshold are considered to be part of the vein structure (Miura *et al.*, 2004) (Figure 3.11c).

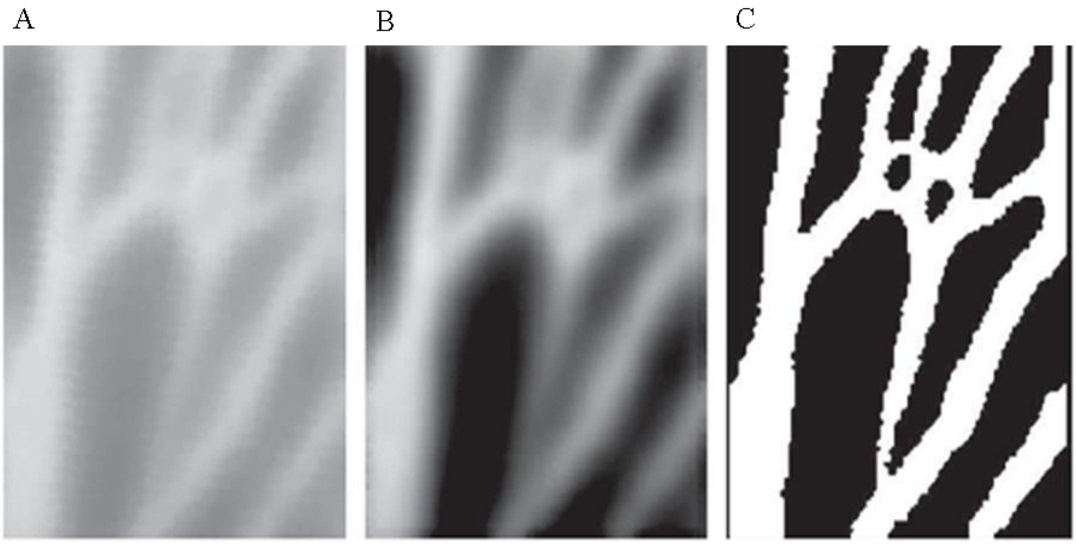


Figure 3.11 Example of FIR hand vein images a) original image b) after noise reduction and normalisation and c) after thresholding (Wang *et al.*, 2008).

The images are then transformed into mathematical templates, which are stored on the database of the biometric system. These templates consist of the vein structures appearing as binary high intensity pixels, with background structures as low intensity structures (Hartung *et al.*, 2011). Templates are stored rather than raw images to reduce the volume of data stored, as well as providing heightened security benefits, in that no original data is stored on a database that could potentially be hacked (Luo *et al.*, 2010).

Feature extraction

To extract the features from a vein pattern, the image is usually skeletonised (Figure 3.12a), created using a thinning algorithm which produces a single pixel wide 'skeleton'. This can produce angular turns which are not truly representative of veins, so a polynomial curve process is applied to smooth the edges (Figure 3.12b).

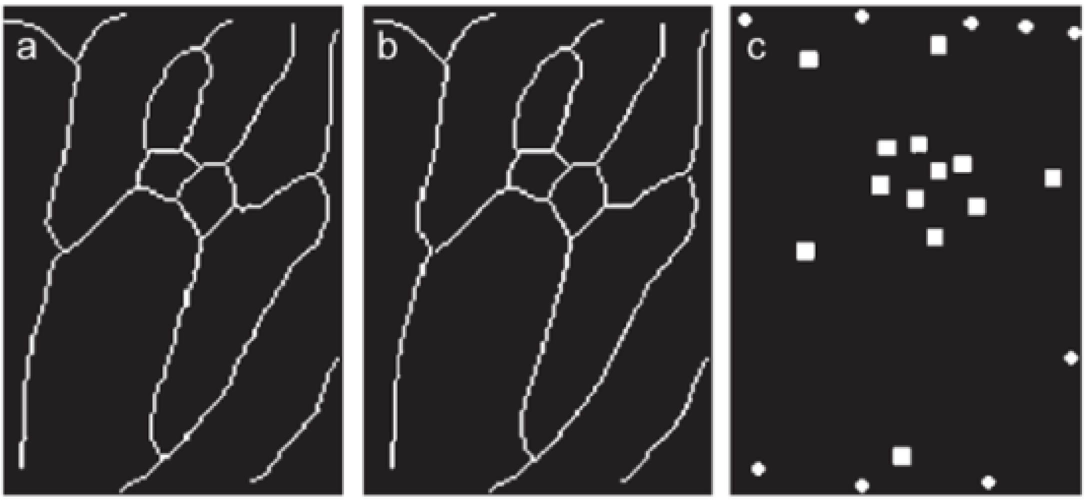


Figure 3.12 a) skeletonised representation of vein pattern b) skeletonised version of vein pattern after application of polynomial curve processing c) minutiae points extracted from skeletonised image. (Wang *et al.*, 2008).

The next step is to extract the minutiae points from a skeletonised version of the vein pattern (Figure 3.12c), which can be achieved in several ways. Wang *et al.* (2008) used branching points and ending points as chosen minutiae to extract from the image. In finger print terms, minutiae are described as the 'randomly placed imperfections' that occur in the overall pattern of the fingerprint such as line endings or bifurcations

(Adam, 2010). A study by Luo *et al.* (2010) found that on average 13 minutiae points are extracted from each dorsal hand vein pattern image, with 7 bifurcations and 6 ending points (Luo *et al.*, 2010, Wang *et al.*, 2008).

During the authentication (or verification) phase, the same information is collected as during enrolment to ensure the system can locate the template correctly from the same users information (Luo *et al.*, 2010). Once authenticated, the user can operate the biometric system; the next time the user operates the system, it will work on a one-to-many matching process, which is followed by the decision making stage. This involves the biometric system defining the individuals' claimed identity as either genuine, and accept the claim, or as an imposter, thus reject the claim (Burghardt, 2009). The decision phase depends primarily on feature matching (depending on the algorithms used), by assessing the similarities between the 'query' image/data and all other images/data on the database; a decision is made based on the computed similarities of the features (Luo *et al.*, 2010; Miura *et al.*, 2004).

Wang *et al.* (2008) set out to assess the ability of each minutiae type as a potential 'identifier', by examining bifurcations and end points in isolation, then cumulatively. They found that bifurcations and end points have relatively high recognition accuracy, but using a combination of both, increases this accuracy (bifurcations only: EER = 2.1%; end points only: EER 2%; both minutiae types: EER = 0%), ultimately concluding that the hand vein minutiae have potential as a discriminating feature in hand vein pattern images (Wang *et al.*, 2008).

A threshold is set within the recognition system, which must be reached or exceeded to verify an identity (Wilson, 2010). If the similarities fall below the threshold, then the user is considered to be an imposter (Luo *et al.*, 2010). Rigorous testing of the system in the development stage is therefore of utmost importance to ascertain the level at which to set the threshold; the larger the database used to determine the threshold will enhance reliability of the system (Luo *et al.*, 2010).

Vein pattern biometrics exploits the high level of variation in the vein pattern features, or minutiae. This has been shown to be performed with a high degree of accuracy. Further to this, it has been shown that more than one type of feature or minutia is more accurate that using just one (Wang *et al.*, 2008).

This support from the biometric literature for the use of vein patterns as a method of identifying an individual forms the basis for this approach to be applied to a forensic scenario.

4.2.2 'Soft' biometrics

In addition to 'classic' biometrics such as fingerprints and vein patterns, scars, marks (including pigmentation) and tattoos have been used as 'identifiers'. With regard to isolated areas of pigmentation, it is possible, as described earlier that these can be distinguished histologically (i.e. the difference between an ephelide and a melanocytic nevi), however, when used as a soft biometric, these features are often examined from a digital image, where histological discrimination is not possible, therefore, in a forensic scenario these features are examined purely on their physical appearance and relative location.

These features are classed as soft biometrics and are described as characteristics that provide some identifiable information, but lack some of the fundamental qualities of a traditional biometric; including the lack of distinctiveness and permanence required to distinguish between two individuals (Jain *et al.*, 2004a; Lee *et al.*, 2008).

Soft biometrics may not exclusively enable identification of an individual, but when used in conjunction with another, or several other, biometric traits, they can be helpful in building a clearer picture of the questioned individual's identity, thus enhancing discrimination.

4.2.3 Multi-modal biometric systems

The biometric systems described thus far have comprised uni-modal biometric systems, whereby only one feature is considered within the system. However, uni-modal biometrics are susceptible to practical problems e.g. noise from sensor data, non-universality, lack of distinctiveness, poor error rate and spoof attacks (Jain *et al.*, 2004a).

Biometric systems reliant on more than one biometric feature are emerging as a progression from the initial, uni-modal systems (The Federal Bureau of Investigation, n.d.), as it is argued that a multi-modal system can acquire more information than a single biometric, thus potentially increasing its performance (Hong *et al.*, 1999; Jain *et al.*, 2004a; Mohammed *et al.*, 2014).

Examples of multi-modal biometric systems include; multiple versions of the same biometric e.g. fingerprints from every finger of an individual; repeats of the same biometric e.g. a fingerprint taken several times; multiple biometric traits used in conjunction e.g. face and fingerprints (Jain *et al.*, 2004a; Ross and Jain, 2004).

A multi-modal system based on different biometric identifiers can be highly effective as it overcomes other multi-modal systems that still encounter problems of using one biometric trait (Lee *et al.*, 2008). This 'true' multi-modal system is thought to be more robust by addressing the issue of non-universality (e.g. some people may have a very simple, or no vein pattern visible); although biometrics are expected to be universal, in reality no biometric can be truly universal (Hong *et al.*, 1999; Ross and Jain, 2004). These systems can improve matching accuracy and enhance protection against spoof attacks (Lee *et al.*, 2008), as it is unlikely that an imposter is able to spoof more than one biometric characteristic (Hong *et al.*, 1999; Ross and Jain, 2004).

Hong *et al.* (1999) found that a multi-biometric system performed better than a single biometric system. These conclusions were drawn from the false acceptance rates which showed that face recognition (FAR = 15.8%) and fingerprints alone (FAR = 3.9%) were out performed by a combination of both characteristics together (FAR = 1.8%). Another example was shown by Mohammed *et al.* (2014), when testing finger vein and iris scanning techniques in conjunction, they were found to have a matching score level of 92.4% accuracy, compared to 86.6% for finger veins only and 75.1% for iris scans only.

These large systems do however present their own issues; the cost of building a system to test all traits in different formats, plus the increased storage of the apparatus to facilitate this, the length of time to collect all the data and finally collection of multiple sets of data may cause inconvenience to the user. For these reasons, multimodal systems are usually restricted to 2 or 3 modalities (Lee *et al.*, 2008).

Nonetheless there is a growing trend in the literature for multi-modal, rather than uni-modal systems. A theme within the Horizon 2020 proposed funding opportunities for research and development includes the development of a multi-modal biometric system to enhance security across EU borders (European Commission, 2013).

4.2.4 Biometric modalities with a forensic application

The examination of anatomical features is used for the purposes of forensic investigations when the identity of an individual must be established. It is argued that this approach is based on biometric techniques, but without the aid of automated biometric systems (Spaun and Bruegge, 2008).

Forensic human identification from images and videos is performed by the Federal Bureau of Investigation’s (FBI) division of Forensic Audio Video and Image Analysis

Unit (FAVIAU) to analyse faces from images. The method involves comparisons of photographic images of the suspect image to the offending image (e.g. photograph of suspect in police custody with CCTV footage of offence). The image examiner locates identifiable features that are observed on the individual to begin to characterise their appearance. These features may be quite general such as the shape of the face, presence of facial hair, presence of freckles, shape of nose etc.; or may be more specific such as the number and location of minutiae including freckles, blemishes, scars, tattoos or wrinkles (Spaun and Bruegge, 2008). Facial mapping involves the assessment of differences and similarities , including the presence or absence of features in the images being compared. Based on these findings, it can be established as to how likely it is that the individuals within the images are the same. It should be noted that similarities may not prove identity, but differences can prove the non-identity. As the similarities increase, the number of people who share the same combination of features, will decrease (National Policing Improvement Agency for the Association of Chief Police Officers, 2009). This approach to image analysis can be applied to images of other regions of anatomy, including the dorsum of the hand.

The FAVIAU follow the method used by fingerprint examiners; analyse, compare, evaluate, and verify (ACE-V). The features in the offender image are assessed, before the features of the suspect are examined. A comparison of the two is then performed, noting any similarities and differences. The examiner then evaluates the significance of the similarities and differences, bearing in mind that differences may be explained by factors including changes in pose, illumination or time between the images. A conclusion is made whether the offender and suspect may be the same individual, are not the same individual or could not be identified or excluded. The findings are then verified by one or more additional examiners (Campbell, 2011; Spaun and Bruegge, 2008).

4.3 Current and innovative anatomical research with forensic application

Due to the lack of extensive description of the DVN in the anatomical literature, and for the purposes of quantifying this variation in this region for forensic purposes, some work has been conducted within the forensic research arena that goes some way to describe the pattern variability in this region. The studies described involve extracting vein pattern information from digital images of different lighting conditions (visible light and near-infrared light).

Meadows (2011) and Aiken (2014) investigated the counts of vein pattern features (or minutiae), reporting the overall density of the vein pattern rather than specific topology. Both studies applied the same (minutiae of vein patterns) nomenclature to parts of the vein pattern; referred to as features herein. ‘Lines’ are regions of visible veins, ‘branches’ denote where a region of vein has bifurcated from another, ‘islands’ are areas entirely enclosed by veins and ‘intersections’ are where two lines cross one another (Figure 3.13) (Aiken, 2014; Meadows, 2011).

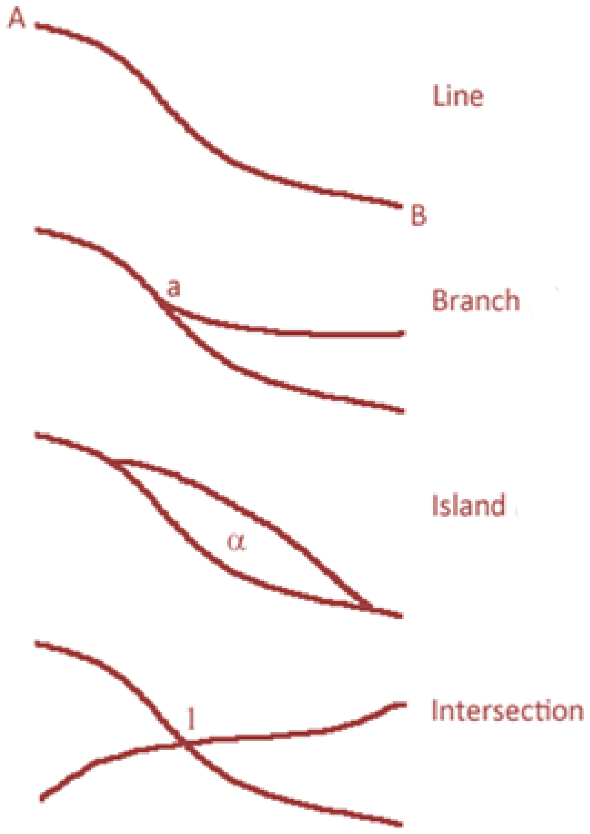


Figure 3.13 Vein pattern features: line, branch, island and intersection (Meadows, 2011).

Meadows (2011) and Aiken (2014) found lines were the most common feature, followed by branches, then islands and finally intersections were shown to have the lowest prevalence. The mean count for 'lines' in the visible light images was 12 or 13.25, dependant on the dataset used (Meadows, 2011). Intersections were shown to be a rare feature within the vein pattern by Meadows (2011) (found intersections in 10% of a visible light sample), whereas Aiken (2014) found intersections in 42% of the sample, from NIR images. Islands were also shown to be a relatively rare feature within a vein pattern by Meadows (2011) (23% of the sample contained islands) whereas Aiken (2014) found significantly more from NIR images (70%).

Further to the studies by Meadows (2011) and Aiken (2014), a study carried out by Donnelly (2014) focussed on the spatial distribution of the vein pattern features across the dorsum of the hand; therefore taking a step towards filling the gap in the anatomical literature with regard to vein pattern topology on the dorsum of the hand. Donnelly (2014) applied a grid structure composed of 9 cells to images of the dorsum of the hand and assessed the spatial distribution of the vein pattern by identifying where the features of the vein pattern resided within the grid cells (Figure 3.14).

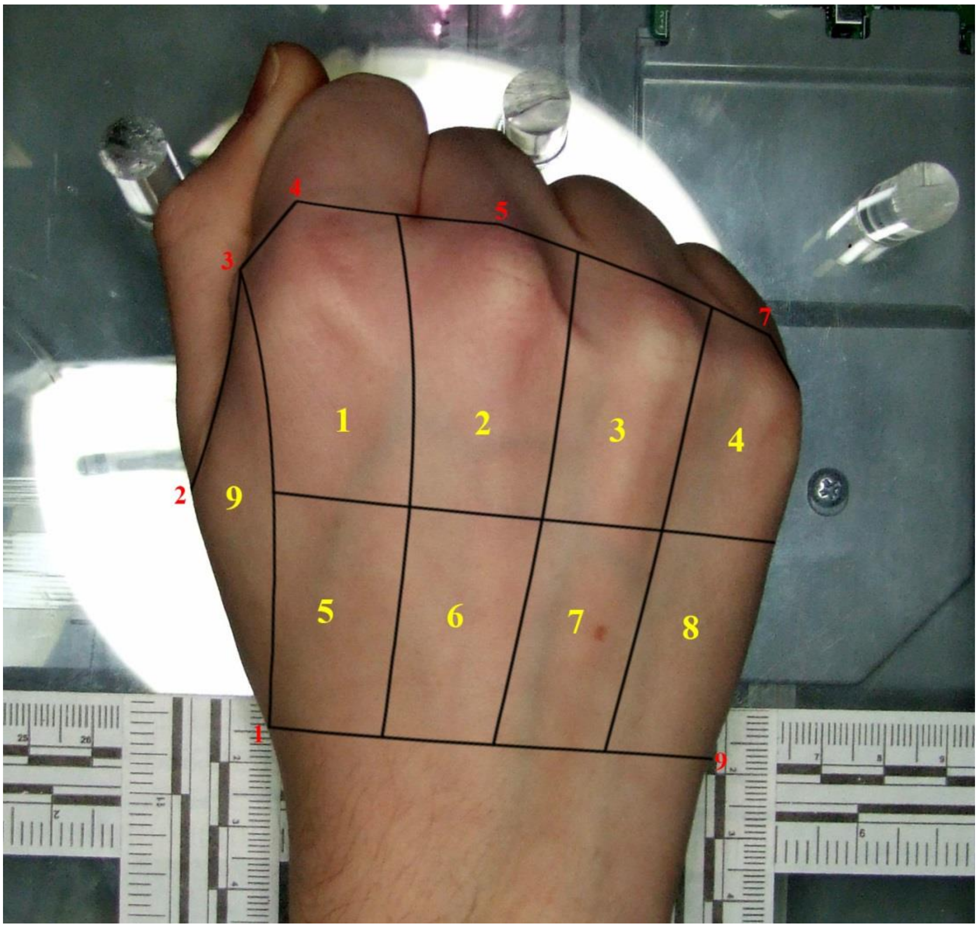


Figure 3.14 Example of grid placement and numbering (Donnelly (2014): Figure 2.6, p 17))

The nomenclature for vein patterns was further developed for the purposes of the study by Donnelly (2014), by referring to start and end points and branching points as 'nodes'. It was found that, based on node density; cell 2 contained the highest density of nodes, followed by cell 7. Cell 3, although did not exhibit the most nodes, was the only cell not to record a value of zero, indicating that this cell consistently contained vein pattern information. Finally, cell 9 exhibited the least amount of information (Figure 3.15).

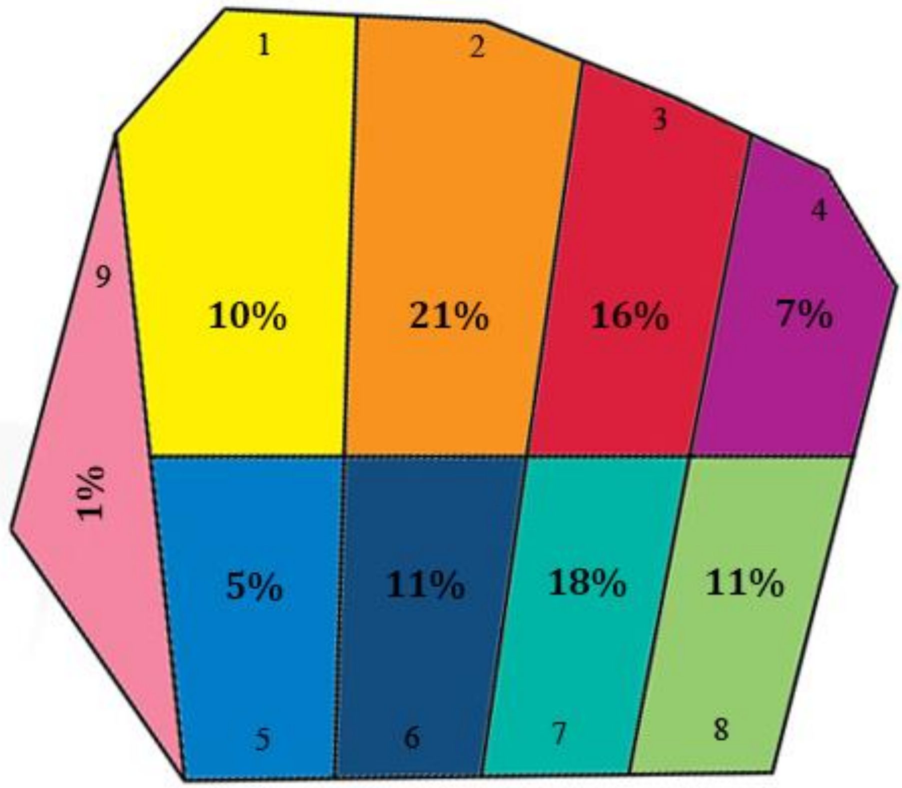


Figure 3.15 Schematic showing the mean percentage density of nodes for each spatial area within the dorsum of the hand. (From Donnelly (2014): Figure 3.11, p 72)

When assessing the proximal-distal distribution with regard to node density, it was found that there was significant overlap in node density between the proximal and distal portions of the hand, suggesting that vein pattern density does not vary greatly between these two areas.

When considering slices of the grid from medial to lateral (cell 1 and 5, cell 2 and 6, cell 3 and 7, cell 8 and 4) it was found that the middle regions, cells 3 and 7 had the highest node density, followed by cells 2 and 6. The lowest density was seen in cell 9, followed by cell 1 and 5.

This informs of the most likely regions of the hand, where vein pattern features will be observed. Despite the obvious benefit in gained knowledge of this work, the exact topology in this region has yet to be explored.

4.4 CAHId case work

The investigative methods employed by the team of forensic experts in CAHId, utilise the superficial vein patterns and surface features on the dorsum of the hand, primarily to establish the level of similarities and differences between images of two individuals who are allegedly involved in a case of CSA (Black *et al.*, 2009; Meadows, 2011).

To ascertain the anatomical differences between the suspect and offender from a digital image, the police provide images of a suspect's hand posed in positions similar to those seen in the offending images, to facilitate a comparison. Similarities and differences are ascertained to determine if the suspect and the perpetrator are the same individual, or if the offender is another, unknown individual (Black *et al.*, 2009). Following the ACE-V process, the offender images are assessed first, focussing on the level of anatomical information contained within these images; the suspect images are subsequently assessed to establish whether the suspect can be excluded from further investigation. This process is entirely 'exclusionary'; a positive identification is never made. For example, it is possible for individuals to share numerous similarities in their anatomical features; however it takes only one, valid difference to exclude an individual as the offender, therefore supporting a suspect's innocence. If no valid differences are found, then the forensic expert explains that 'the suspect cannot be excluded as being the offender' (Black *et al.*, 2009).

A review of the cases carried out at CAHId to date show that in forensic case work, a multi-modal approach is often employed due to the level of detail available within the presented images. Figure 3.16 shows that the three most frequently used features were knuckle creases, vein patterns and pigmentation. In the majority of cases (26%) six different feature types were used, in a further 21.7% of cases, two or three features were used. In only 8.6% was one feature type used.

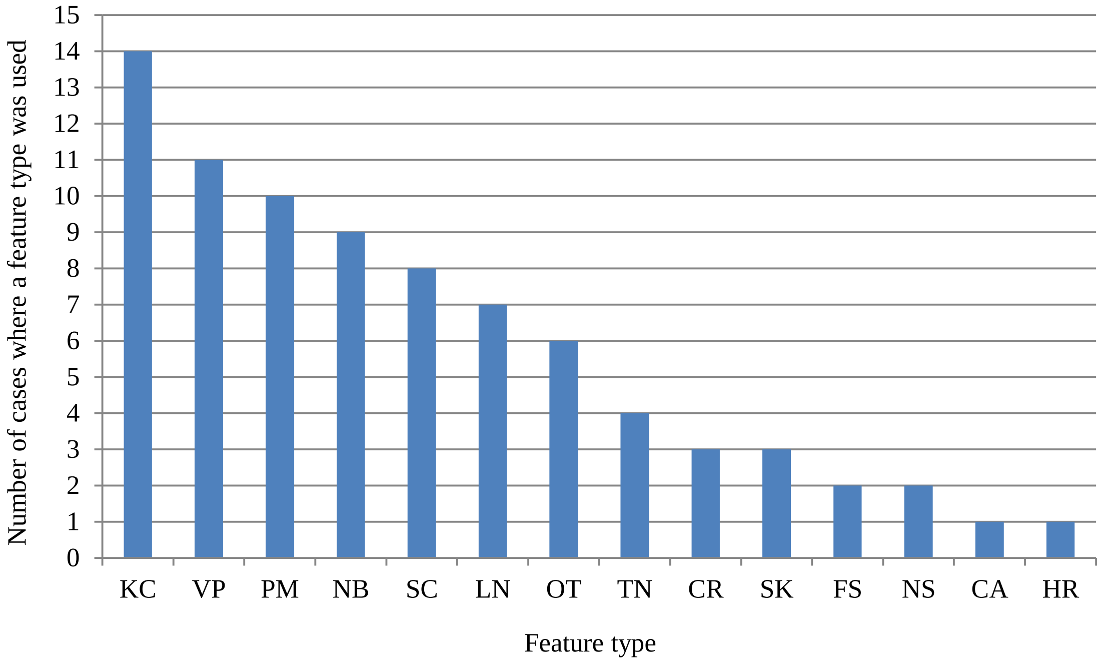


Figure 3.16 Anatomical features used in forensic cases conducted in CAHId involving the assessment of the dorsum of the hand. KC: knuckle creases, VP: vein patterns, PM: pigmentation, NB: nail bed, SC: scars, LN: lunule, OT: other, including skin discolouration or reddening, arthritic joint and cuticle area, TN: tendons, CR: palm creases, SK: skin colour or tone, FS: finger shape and/or size, NS: nail shape, CA: callouses, HR: hair.

In many of the cases conducted in CAHId, the images were taken on a mobile phone device. These days the majority of images are captured on a mobile phone; 60.1% of the human population is estimated to own at least one mobile phone, and 83% of those contain a camera phone (Ahonen and Moore, 2013). More than 90% of all humans who have taken a picture have only done so on a camera phone and not on an actual camera

(Ahonen and Moore, 2013). This can provide difficulty in comparing images, as the suspect image is often of higher quality than the offender image.

The content of case work has driven a series of research projects within CAHId, with the common aim of strengthening support for forensic human identification on the basis of vein pattern and surface feature anatomy variability.

Meadows (2011) established a systematic method for recording the superficial vein pattern, which formed the basis for the methodology used in forensic case work. Subsequent research sought to quantify the spatial distribution of the vein patterns (Donnelly, 2014) and the effect of different imaging conditions on the visibility of the vein pattern (Aiken, 2014). Other projects have investigated the use of surface features as identifiers, including the position, size and shape of areas of isolated pigmentation and scars (Macdonald-McMillan, 2011) and the crease patterns created by skin folds over the interphalangeal joints (Nicoll Baines, 2012). Research to date has primarily been concerned with one group of features, however, consideration of a multi-modal approach to human identification has not been explicitly examined, despite the fact that this is the most common approach in case work.

A study by Pearson (2014) tested observer performance with regards to hand feature analysis for forensic purposes. Performance was tested by the ability of observers to correctly identify a hand image, from a pool of possible images. To arrive at their decision, observers were instructed to utilise all features they deemed necessary; this lack of direction was to establish which features were employed by an untrained observer, versus an expert in the field.

It was found that expert observers were more likely to rely on features that are known to have discriminatory capabilities such as vein patterns, knuckle creases and pigmentation; whereas the inexperienced observers either did not provide extensive details regarding their decisions making process, or relied on features that are thought to be less discriminatory such as skin tone and size of the hand or fingers. Some inexperienced observers did use features such as pigmentation, but were not as confident in their decision.

Despite this finding, statistical testing showed that there were no significant differences in correct identifications from the untrained observer group compared to the expert group.

4.5 Observer bias and reliability

The application of biometric methods to the forensic arena is a feasible collaboration. The two industries share fundamental objectives such as, the requirement for low error rates and high accuracy. However, a biometric system is usually concerned with authentication of a ‘known’ identity of an individual against a claimed identity, which differs significantly from a forensic investigation, where it is often a one-to-many match situation and an exclusive identification is not usually made. Additionally, a biometric system operates on an automated or semi-automated system that has undergone rigorous testing for reliability and accuracy. Most forensic situations (currently) rely on a human operator; a system which is inherently open to bias and error.

The human operator as a source of error is an issue which has been discussed in the forensic literature. In the National Academy of Sciences (NAS) report (which will be discussed in more detail in subsequent sections of this thesis), it was stated that there was a lack of research in forensic science specifically focussed on the subjectivity and reliability of forensic methods and techniques (Dror *et al.*, 2006; National Research Council of the National Academies, 2009). Subsequent forensic literature has seen an increase in research related to the effect of contextual information with regards to forensic examiner bias (Page *et al.*, 2012).

It is difficult to retain impartiality and detachment from a case scenario in a forensic investigation; however it is important to do so, to ensure that the evidence in question is examined as objectively as possible. Observer bias can still be a factor for the forensic practitioner, who is not directly involved in the investigation, only the assessment of evidence,

Observer, or cognitive bias is described as the “psychological sway toward one opinion versus another as a result of having information extraneous to the task at hand” (Page *et al.*, 2012). It has been shown that particularly emotive cases can enhance the level of bias to which experts can succumb subconsciously (Dror *et al.*, 2005).

Page *et al.* (2012) suggest several ways in which cognitive bias can be minimised including; avoiding contact with the victim, law enforcement agencies and lawyers and minimising the level of case detail known to the examiner, as this may minimise the emotive effect.

An approach presented by (Jackson and Black, 2014) introduces the evaluation and reporting of surface feature evidence in a logical manner. Taking a step beyond the reporting of similarities and differences between two images, this paper demonstrates how such data can be used to inform probabilities, so that an evaluative opinion in the form of a likelihood ratio (LR) can be provided. The principle is based upon Bayes theorem, whereby newly acquired information can be used to update the probability of an uncertain event, which is useful in a judicial scenario as it can be used to assess the weight of evidence.

The LR is the ratio of the probability of the experts observations, given an allegation to be true, to the probability of achieving the same observation, given an alternative proposition were true. For example, the likelihood that the hand seen in the offending image belongs to the individual in police custody, to the likelihood that the hand belongs to another unknown person.

Using previously collected databases it is possible to assign probabilities regarding the presence of a particular set of features based on precise statistics, whereas probabilities based on case specific information involved a manner of subjectivity (Taroni *et al*., 2001). This approach ensures a logical and robust interpretation of expert evidence. In some cases a statistical model can be used to form a probabilistic basis for conclusion, however in other scenarios, a more subjective approach is the only available technique (The Forensic Science Regulator, 2014).

The Scientific Working Group for Imaging Technology (SWGIT) set out a format which can be used to relate the findings from image comparison when a statistical approach is not possible, depending on the subjective opinion of the expert (Scientific Working Group on Imaging Technology, 2009) (Table 3-3). This ensures continuity in reporting a subjective opinion in such cases.

Table 3-3 Continuum of conclusions for image comparison. (adapted from Scientific Working Group on Imaging Technology (2009))

Continuum of conclusions examples for photographic comparative analysis		
Inclusion	Similar	Powerful support
		Strong support
	No conclusion but with similarities	Moderate support
		Limited support
No conclusion	No conclusion	inconclusive
Exclusion	No conclusion but with dissimilarities	Limited support
		Moderate support
	Dissimilar	Strong support
		Powerful support
No comparison possible		

4.6 Network analysis

In an attempt to quantify the vein pattern in a more objective manner, network analysis was employed for this research.

Network analysis (NA) is a form of multivariate statistical analysis that uses a collection of objects (nodes) and their inter-connections (edges) to describe the overall structure of a complete unit; termed a network.

The study of networks was founded on a branch of mathematics known as ‘graph theory’ (Albert and Barabási, 2002; Boccaletti *et al.*, 2006). Specifically, the Erdős model was first used to study random graphs introduced by Erdős and Rényi in 1959. This model was based on probabilities, used to assess the connections possible within a random network (Albert and Barabási, 2002; Boccaletti *et al.*, 2006) where every possible node, ‘N’ in a network is connected with the probability ‘*p*’ (Erdős and Rényi

(1961) cited in Itzkovitz *et al*. (2003)) and can be summarised in the following equation: $\frac{pN(N-1)}{2}$ (Albert and Barabási, 2002).

Researchers believed that the graph theory models did not represent accurately the ‘real world’ systems they were investigating and were therefore flawed in predicting the functional activity of the systems (e.g. biological processes). Following this realisation, research was directed towards the development of new models to mimic growth, development and structural properties in real world systems.

In recent years, interest and research towards the study of networks has expanded, facilitated by increased power of computer technology and the ability to produce and analyse large databases of real networks (Boccaletti *et al.*, 2006).

Structure of networks: Overall structure

The ‘degree’ of a node is the number of connections it possesses with other nodes; often some nodes are more connected than average (Barabási and Albert, 1999; Boccaletti *et al.*, 2006; Milo *et al.*, 2002; Newman, 2001). The overall complexity of a network can be expressed by the number of nodes and edges. However, it could be assumed that ‘complexity’ is better described by the ‘local topology’ of networks, by the motifs, or sub-graphs (Juszczyszyn *et al.*, 2008) and nodes and edges can be used to describe the ‘density’ of a network.

Local topology: Motifs

A motif is a collection of nodes and edges that create distinctive structure within a larger network, which can be made up of three or more nodes, with the edges arranged in various permutations between the nodes. A type of sub-graph or motif, termed ‘induced sub-graph’ by Tran *et al.* (2014) defines motifs that are mathematically identical, but possess different shapes. This can occur when there are the same number of nodes and edges but the connections between the nodes differ, thus producing a different topology.

Motifs can either be directed or undirected, examples of which are shown in Figure 3.17. An undirected motif contains no information regarding the direction of the edges. A directed motif contains arrows on the edges, which denote that an edge has a defined start and end point. In a directed network it is possible to distinguish between an in-coming edge (in-degree) and the out-going edges (out-degree) of each node (Buchanan *et al.,* 2010). Non-directed networks have edges with no specified directionality, which allows only two types of 'triad' or '3-node motif'; characterised by a triangle and the shape of the letter 'v' (Milo *et al.*, 2004).

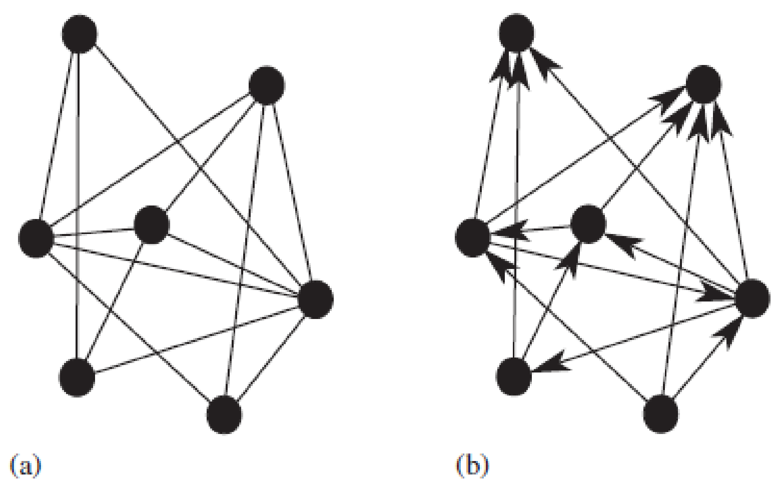


Figure 3.17 Examples of a) an undirected 'graph' and b) a directed 'graph'. (adapted from Boccaletti *et al.*, (2006), figure 2.1.)

Quantitative analysis of networks can be useful in many ways, one example is the ability to group or classify networks. This can be achieved by labelling each node with an integer number '*i*' to establish the topology of the network and its motifs. The relative frequencies of these motifs can be used to divide networks into 'super families' of networks, to categorise networks to aid interpretation of the function of the larger network (Buchanan *et al.*, 2010; Milo *et al.*, 2004).

Where are networks found?

Networks exist in many systems, both in nature and man-made. In nature; from biochemistry (interactions between transcription factor proteins and the genes they regulate (Alon, 2007; Maslov and Sneppen, 2002; Shen-Orr *et al.*, 2002; Szallasi, 1999)); neurobiology (in the nervous system where the nerve cells represent nodes which are connected by axons (Koch, 1999)); to ecology (food webs) (Milo *et al.*, 2002; Montoya and Ricard, 2002; Newman, 2001). Examples of man-made systems include the World Wide Web, where webpages are the nodes and hyperlinks are the edges (Albert and Barabási, 2002; Broder *et al.*, 2003; Milo *et al.*, 2002; Newman, 2001) and social networks where nodes are human beings and edges are the various social relationships (Albert and Barabási, 2002; Hong-lin *et al.*, 2014; Juszczyszyn *et al.*, 2008). In the field of gene transcription regulation, motifs serve as the basic building blocks of the transcriptional networks where nodes represent proteins and genes whilst the edges represent the chemical interactions that occur between these structures (Weng *et al.*, 1999).

The vein pattern as a network

As described, many systems both with nature and man-made systems can be represented and therefore analysed as a network potentially. This extremely valuable data analysis tool can be applied to any structure with connected objects.

A vein pattern can be considered to be a network, as it contains structural features (‘nodes’), i.e. the start and end points of veins, points of bifurcation, or points of intersection, which are connected by areas of visible vein (‘edges’).

A pattern that the superficial veins create can be described as a directed network, as the 'direction' of blood flow can be assumed using physiological and anatomical knowledge (with the exception of transversely location veins, which are given bi-directionality as the direction cannot be assumed).

4.7 Applicable Law and Evidential Admissibility

Forensic science in court

"Forensic science is science used for the purposes of the law" (House of Commons Science and Technology Committee, 2005), more specifically it relates to the "application of scientific methods and techniques to the investigation of crime" (Oxford Dictionaries, 2014), to support the trier of fact (The Ministry of Justice, 2014).

Law and science, as two separate disciplines, are required to work together in the context of a forensic investigation. This often proves difficult when the two disciplines attempt to understand one another, for example, terminology such as 'evidence', 'opinion' and 'reliability' have different connotations for scientists and lawyers. It is therefore important to understand the law that applies to forensic science for the purposes of this research. This chapter will address the role of the forensic scientist as an expert witness in the legal framework, the issues faced by an expert and how expert evidence is reported, specifically in criminal cases. Secondly, areas relevant to the admissibility of expert evidence, and how this has evolved in response to high profile cases will be discussed.

The expert witness and expert evidence

Within the procedure of a criminal trial an expert witness may be called upon to provide opinions which may assist in resolving issues concerning a specific area of knowledge, which can only be acquired by special training or experience (Health and Safety Executive, 2003).

To warrant the presence of an expert witness in court proceedings, the interpretation of the results presented (e.g. results from scientific tests) should be outside the experience and knowledge of the jury and judge, but be within the understanding and expertise of the expert (House of Commons Science and Technology Committee, 2005). This can constitute the experts providing their professional opinion, supported by their findings (Doak and McGourlay, 2009). In Scottish law Davidson (2007) states that while experts are often individuals with some eminence in their particular field of science, there is no need for a witness to possess recognised qualifications to be regarded as an expert.

The purpose of the expert is to provide scientific criteria upon which conclusions are based, to enable the judge or jury to arrive at their own judgement on the application of these criteria to the evidence (The Forensic Science Regulator, 2012).

The expert has an overriding duty to assist the court, as triers of fact, irrespective of their employer's or anyone else within the proceedings. This includes the defendant, or the Crown, that has called upon their expertise and any opposition who may instruct them throughout the trial (Crown Prosecution Service, 2010; House of Commons Science and Technology Committee, 2005; The Ministry of Justice, 2011).

Where either the defence or prosecution chooses to rely on expert evidence, the trial judge must determine, firstly, if the expert opinion is necessary, and secondly, whether the witness is adequately qualified (Doak and McGourlay, 2009).

Admissibility of expert evidence

The admission of evidence is determined by the court, or the judge. Before admissible evidence can be derived it is important to establish the validity of forensic and scientific techniques. This is the case for all types of forensic evidence, both well-established disciplines and new and emerging techniques. Over the last century forensic evidence has progressed and consequently, the applicable law has had to evolve to accommodate changes.

4.7.1 Admissibility in the United States

To illustrate the current state of admissibility of expert testimony there are a number of high profile U.S. cases that highlight the importance for governance of the admissibility of expert evidence in court.

Frye vs. United States, 293 F. 1013 (1923)

The case of Frye vs. United States brought to light issues pertaining to the admission of scientific evidence in court, when the validity of the polygraph test (precursor to the lie detector) was questioned.

In this case, the defendant, James Frye was convicted of murder, but appealed the verdict. The defence counsel proposed that an expert witness should present the results of a polygraph test carried out on the defendant, but this was denied by the court. The defendant argued that the use of this test lay within the boundaries for admissibility in court, as the opinions of experts or skilled witnesses were admissible in evidence, when an inexperienced person is unlikely to be capable of forming a correct judgement upon it (Frye vs. United States 293. F 1013, 1923).

However, the court stated that this test was not yet fully recognised or supported by the scientific community and therefore it could not be admitted as evidence in court. They stated that "[the evidence on which an expert forms their opinion] must be sufficiently established to have gained general acceptance in the particular field in which it belongs" (Frye vs. United States 293. F 1013, 1923). Frye's appeal was subsequently rejected and he was convicted of second degree murder.

It was from this statement that the ‘Frye standard’ was established and adopted by many U.S. states. It stated that evidence was admissible if it was based on methods and techniques that were ‘generally accepted’ (Gebauer, 2004).

Federal Rules of Evidence (FRE)

Over time and with the advancement of science, the Frye standard was gradually adapted or even ignored by the courts (Christensen, 2004). To re-establish the guidelines for expert evidence in criminal and civil trials in U.S. federal courts, the FRE were introduced in 1975 (Christensen, 2004). Specifically the FRE rule 702 relates to expert witness testimony and states that; “A witness who is qualified as an expert by knowledge, skill, experience, training, or education may testify in the form of an opinion or otherwise if:

(a) The expert’s scientific, technical, or other specialised knowledge will help the trier of fact to understand the evidence or to determine a fact in issue;

(b) The testimony is based on sufficient facts or data;

(c) The testimony is the product of reliable principles and methods;

(d) The expert has reliably applied the principles and methods to the facts of the case.”

(United States of America Government, 2012)

Although the FRE set out guidelines for criminal and civil proceedings, confusion remained as to its application. Some were of the belief that it did not incorporate the Frye standard, and that it had established an entirely new set of rules. This led to disagreement across the legal system, with some states adopting the Frye standard, some adopting the new FRE, and in some cases a combination of the two. This unrest and confusion across the legal community led to discrepancies (Christensen, 2004; Gebauer, 2004).

Daubert vs. Merrell Dow Pharmaceuticals Incorporated, 509 U.S. 579 (1993)

The Frye standard was superseded in many, but not all U.S. states by the case of Daubert v Merrell Dow Pharmaceuticals. Following this case it became the legal precedent in the U.S. Supreme Court that evidence must be subject to peer review and publication, and generally recognised as 'sound' by the relevant scientific community (Wall, 2010).

The Daubert decision highlighted that the judge may act as a 'gatekeeper' allowing him/her to scrutinise proposed expert testimony and eliminate it where it does not fulfil the standards of reliability on the grounds of addressing its scientific validity and relevance (Gebauer, 2004; Hileman, 2003).

This formed the basis of a general framework by which the admissibility of expert testimony could be assessed, and became known as the 'Daubert factors':

- The expert's theory or technique can or has been tested.
- The theory has been subjected to peer review and publication.
- The testimony should state a known or potential rate of error.
- The testimony should outline the existence and maintenance of standards and controls.
- The methods should be generally accepted by the scientific community in which it is held.

(Daubert vs. Merrell Dow Pharmaceuticals 509. U.S. 579, 1993; Gebauer, 2004)

The 'gatekeeper' role of the judge allows flexibility in the admission of evidence. For example, techniques do not have to have been published to be admitted, as publication does not necessarily ensure that methods and conclusions are reliable. However, the process of peer review allows methods and techniques to be scrutinised by peer experts, therefore it should increase the likelihood of any errors or flaws being detected (Christensen, 2004).

General Electric Company vs. Joiner 522 U.S., 136 (1997)

Another influential case in determining the admissibility of forensic evidence in court is that of General Electric Co. vs. Joiner.

The testimony from the expert called by the appellants was deemed inadmissible as the court believed that it did not rise above subjective belief or unsupported speculation. Using the Daubert standard, the Court excluded the expert's testimony because it drew different conclusions from that of research in the area. This case did however expand on the Daubert ruling, in that it deemed the methodology and the expert reliable, yet stated that there was a significant gap between the data and the expert opinion given (Gebauer, 2004; General Electric Company vs. Joiner 522 U.S. 136, 1997).

The court of appeal (COA) stated that it is the duty of the Court to determine the legal reliability of the expert testimony, and the responsibility of the jury to decide the correctness of competing expert opinions; therefore qualifying the roles of the court and the jury with regard to interpreting evidence.

Carmichael vs. Kumho Tire Company Ltd., 1999

In the case of Carmichael vs. Kumho Tire Co., the testimony provided by the expert called on behalf of the appellants was excluded on that grounds that it did not comply with the Daubert standard. In this case, they needed to ascertain if Daubert would be applied to specialist technical knowledge as well as scientific knowledge (Carmichael vs. Kumho Tire Company Ltd., 1999).

From this case it was established that a trial judge had the authority to determine whether, and to what extent, the Daubert factors and the FRE are applicable to all types of expert evidence including technical and scientific, and that the Daubert factors can be flexible across disciplines, as long as the testimony is based on reliable knowledge and experience of the relevant discipline (Christensen and Crowder, 2009).

Impact of these cases in the U.S.

These landmark cases set the legal precedent for evaluating the admissibility of expert testimony both in the U.S. and the U.K. (Christensen and Crowder, 2009). In the U.S., this was documented in the National Academy of Sciences report in 2009.

National Research Council of the National Academies report (2009)

The National Academy of Sciences (NAS) 2009 report entitled 'Strengthening Forensic Science in the United States: A Path Forward', sought to address recurring issues within the forensic science discipline and to alleviate the confusion caused by Frye, FRE and Daubert standards (National Research Council of the National Academies, 2009).

The development and implementation of forensic science as a discipline had enhanced the ability of law enforcement agencies to identify perpetrators of crime and collect and analyse circumstantial evidence. However there are many instances where forensic science methods and opinion have been applied incorrectly or inappropriately leading to serious miscarriages of justice. There was also a danger that the weight of evidence could be unclear due to imperfect methodologies and testing and even that forensic evidence can be misleading or even exaggerated.

Due to these concerns the U.S. Congress instructed the committee to address the following points;

- Make recommendations for maximising the use of forensic technologies and techniques;
- Make recommendations for programs to encourage the development of qualified practitioners;
- Disseminate guidelines for best practice on all aspects of forensics to ensure high quality and consistency;

Due to the range of disciplines within the field of forensic science the methods, practices and techniques used are copious and wide ranging. One overriding problem is that not all forensic interpretations are based on scientific studies, with some areas lacking peer review or published studies that establish the validity of their methods. This issue becomes more apparent when forensic interpretations are relayed in court in criminal investigations, as gaps in knowledge or errors in methodology will be exploited quickly by the opposition in court.

Due to the diversity of the forensic science field and the array of issues within them, it was suggested a new entity was established to address these issues, as well as providing support and to oversee and direct the forensic science community. The National Institute of Forensic Science would be responsible for the development of forensic science, founded on systematic collection and analysis of relevant data by enforcing best practices, establishing standards for accreditation and certification of practitioners and promoting peer reviewed research among many other directives.

A fundamental flaw that emerged from this report was that it seems that judges and other members of the legal proceedings do not understand the science behind expert evidence and therefore place too much trust in the evidence; whereas with additional knowledge it may be questioned. This admission made by Edwards (2010) recognises, after in depth review of the forensic science community as part of the NAS report, that the quality of practice across forensic discipline varied widely, and that conclusions drawn are not always reliable.

4.7.2 Expert evidence in England and Wales

The impact from the U.S. cases and their outcomes reverberated not only in the U.S., but also in the U.K. This impact shall be discussed in the following sections, but firstly the differences in legal procedures within the U.K. must be outlined.

Expert evidence in English and Welsh law

Law in England and Wales states that the expert must aid the court to achieve the overriding goal, by providing objective opinion on matters within their expertise, and in doing so they must disregard any obligation to the person who has paid or is instructing them (The Ministry of Justice, 2011). The responsibilities of the expert witness are currently governed by the Criminal Procedure Rules in England and Wales.

When more than one party wishes to introduce expert evidence, the court may direct the experts to discuss the issues, and prepare statements for the matters on which they agree and disagree (The Ministry of Justice, 2011). Within the trial proceedings, the general rule is that the trial judge is responsible for questions of law; competence of the witnesses and admissibility of evidence. Whereas the jury is responsible for questions of fact; credibility of a witness and the weight to be attached to the evidence (Doak and McGourlay, 2009).

It is important to now discuss a selection of cases that have highlighted inconsistencies and flaws in the way expert evidence is presented in courts in England and Wales.

R v Clark EWCA Crim 1020 (2003)

The case of R v Clark was given grounds for an appeal to a murder conviction, based partly on statistical evidence relating to the likelihood that two deaths of infants from natural causes in the same family was flawed, as it misled the jury by overstating the rarity of these two events.

During the appeal, another expert stated that the way in which the original figure was calculated was an over simplification and that other circumstances within this issue had not been taken into consideration. This had breached the court rule, that an expert should not give evidence on matters outside their field of expertise.

This case coincided with two other infant death cases (*R v Cannings EWCA Crim 01* (2004) and *R v Anthony EWCA Crim 952* (2005)); these 3 cases sparked a backlash in the media against this type of evidence and resulted in a review of 297 cases where convictions were based on opinion evidence.

R v Dallagher EWCA Crim 1903 [2003]

The case of R v Dallagher involved ear print evidence which allegedly placed the accused at the crime scene; evidence which played a major role in the decision of the jury to convict the accused of murder. An appeal was later granted on several aspects of the original case. Firstly, that the jury should never have heard the expert evidence on which the Crown relied, as it was inadmissible on the grounds that ear print evidence was in relative infancy, and one of the experts had no formal training in ear print examination. Secondly, because there were no experts for the defence; the evidence relied upon by the Crown was presented in a way that was too favourable to the prosecution and therefore committed a ‘prosecutors fallacy’. Finally, it was ruled that the judge was wrong to admit evidence from previous offences.

An expert who presented evidence at the appeal stated that ear print evidence cannot be used alone to base the identification of an individual at the scene of a crime, but could be used to assist in the early stages of the investigation to eliminate suspects. It was noted that it was not necessary to exclude the ear print evidence, but the value of the conclusion was questionable. The conviction was subsequently quashed, but a re-trial was recommended.

Forensic Science on Trial Report (2004-2005)

Prior to the release of the NAS report, the House of Commons science and technology committee produced ‘Forensic Science on Trial’, which set out to address issues in forensic science. The recommendations that emerged from this report were that there should be enhanced communication between the scientific and legal professions for the on-going scrutiny of expert evidence and called for the establishment of a forensic science advisory council to serve as a regulator for the developing market in forensic science and as an independent source of advice.

Importantly, the committee suggested that there was room for improvement in the way that statistical evidence, including risk and probability are presented to juries. There was a call for U.K. courts to adopt a strategy similar to the Daubert standard in the U.S., as it ensures that expert evidence comes under more focussed scrutiny at an earlier stage in court proceedings. The committee understood that judges are not well placed to assess scientific validity without input from scientists and proposed that the forensic science advisory council should develop a ‘gatekeeping’ test for expert evidence, developed on the basis of the U.S. Daubert test.

Association of Forensic Science Providers (AFSP) Standards

The AFSP produced a set of standards in 2009, outlining the ‘best practice’ recommendations for forensic experts. They proposed that an expert should base their opinions on four principles; balance, logic, robustness and transparency.

To uphold balance, experts should consider at least one pair of propositions (the prosecution and the defence stance). To ensure the process is carried out logically, the expert should address the probability of the evidence given these propositions and any relevant background information. To maintain a robust approach, the expert should provide an opinion that is based on sound knowledge of evidence type and with the use of verified databases, wherever possible. Finally, to remain transparent in their practice, the expert must demonstrate how they arrive at their conclusion(s) and should state the basis of their opinion. This must include any data they have used to arrive at their conclusions and its origin (Association of Forensic Science Providers, 2009).

Despite this guidance, the issues persisted with the presentation of expert evidence, as was seen in the case of R v T.

R v T EWCA Crim 2439 (2010) [Original case redacted online]

The case of R v T is an example of how forensic evidence was presented incorrectly to the courts. The expert had used methodology involving the calculation of likelihood ratios to arrive at a conclusion (in accordance with the Forensic Science Service (FSS) standards), however these calculations were not included in the experts written report or in verbal communication with court, but instead were relayed in a “more understandable” way to the jury using a scale developed by the FSS (Redmayne *et al.*, 2011).. Arguably, the evidence itself was not flawed but the expert had adopted a reporting protocol that obscured the way in which he had formed his conclusions (Redmayne *et al.*, 2011).

The COA concluded that likelihood ratios should be used only in relation to DNA evidence (and any other discipline where it has been shown to be reliable) and instead suggested that the expert give a more evaluative opinion. This judgement was strongly opposed by forensic experts (ref), who state that probability theory provides the only coherent logical foundation for the interpretation scientific evidence (ref), and that the production of likelihood ratios be the most appropriate foundation for assisting the court in establishing the weight of evidence.

It was argued that the COA proposed conflicting ideas; it rightly suggested that full transparency is required in an expert's written reports, but also said that experts should not use LR to come to their conclusions.

This case highlighted the flaws in the presentation of the expert witness's testimony and made a positive contribution to English law with regard to promoting critical scrutiny to the quality of data used in presenting expert evidence. However it also addressed the unreasonable direction of the COA and highlighted the need for scientists and the courts to agree on what is admissible to enable forensic evidence to assist the court.

Law Commission Report 2011

Following continued unrest in forensic science, the Law Commission report of 2011 for England and Wales set out to address the law relating to expert evidence in criminal proceedings after a call for reform from the House of Commons Science and Technology committee from which a draft Criminal Evidence (Experts) bill was proposed.

It was agreed that expert evidence was being admitted too readily and with insufficient scrutiny (The Law Commission, 2011). It was proposed that there should be greater scrutiny at the admissibility stage of court proceedings, in the form of an admissibility test which echoed that of the U.S. Daubert test. It was recommended that this test be founded on the principle that an expert's opinion evidence would only be admissible in criminal proceedings if it was sufficiently reliable.

The new reliability test would allow expert opinion evidence to be admitted, only if it was sufficiently reliable based on whether the opinion was 'soundly based', and 'the strength of the opinion is warranted having regard to the grounds on which it is based'. Furthermore, it was stated that expert evidence should only be admitted if it has sufficient probative value (The Law Commission, 2011).

It was also stated that it should be the responsibility of the trial judge to determine whether an expert's opinion is sufficiently reliable by ensuring that evidence was based on sound data, valid methods, methods had been subject to peer review and that the material was within the experts field of expertise among other points.

The proposed new test would ensure forensic evidence was scrutinised suitably with the intention that this would reduce the number of miscarriages of justice and safeguard public confidence in the criminal justice system (The Law Commission, 2011).

The government responded to the report recommendations by sharing the concerns of the commission, about the unreliable use of expert evidence, and recognised the potential benefits of a reliability test; however, it had concerns regarding subsequent costs incurred from inevitable pre-trial hearings. With no room to save elsewhere whilst incurring these additional costs, the government stated that with current resource constraints, it was not feasible to implement the proposed reliability test at this time. Despite this, there was the suggestion that the criminal procedure rules (part 33) be amended to incorporate some of the suggestions from the law commission report, including providing judges with more information at the beginning of proceedings to aid in the decision of whether to adduce evidence. The government appreciated that this was a shortfall with regard to the extent of recommendations made by the law commission; however this will go some way to remedy the current situation with current resources available.

In late 2014, the updated criminal procedure rules were published, with the expansion of rule 33.2 to include more specific details regarding how the expert should clarify what lies within their area of expertise. A new rule was introduced (rule 33.3), that outlined how expert evidence should be presented to the court and stipulations to ensure transparency of evidence admitted.

The Forensic Science Regulator (FSR)

The Forensic Science Regulator is sponsored by the Home Office, but operates as an independent entity. The post was established to ensure that forensic science provision in the criminal justice system upholds an appropriate level of scientific quality standards (Gov.uk, n.d.), and to standardise forensic science in the criminal justice system in England and Wales (The Forensic Science Regulator, 2008). However, as yet, the FSR does not hold statutory powers, and therefore cannot mandate changes to practice (Home Office, 2013).

4.7.3 Expert evidence in Scottish law.

Whilst efforts have been made to scrutinise and formalise admissibility of expert evidence in England and Wales, the situation remains relatively unresolved in Scotland.

In general opinion evidence is not admissible in criminal courts in Scotland; witnesses may only provide evidence on matters within their direct knowledge, with the exception of a professional opinion.

Part XII of the Criminal Procedure (Scotland) Act 2005 (plus amendments made in 2010) makes no reference to expert evidence other than in relation to experts called to assess the psychological behaviour of the complainer (Scottish Government, 1995). There are no detailed rules as to who may testify as an expert in Scottish Law (Levy and McRae, n.d.). It is the duty of the judge to decide whether an expert is suitably qualified, usually based on qualifications and experience, both which are open to scrutiny by cross examination.

Expert evidence is admitted, if the matter in discussion cannot be resolved, or a conclusion made without instruction or advice from an individual with particular knowledge or experience (Crown Office and Procurator Fiscal Service, n.d.; Sinclair, 2013). Secondly the subject matter must be part of a recognised body of science or experience (Sinclair, 2013).

As in England and Wales, the expert should be independent and uninfluenced by the either party instructing them, should be unbiased, objective and provide opinion only on matters within their expertise. If opinion is based on material that is not properly researched or supported by insufficient data, this should be made clear (Sinclair, 2013). In Scotland, disclosure of relevant material to the defence is an essential requirement for a fair trial in all criminal proceedings (in accordance with Article 6 of the European Convention of Human Rights); failure to do so can lead to the potential for the conviction to be quashed upon appeal (Crown Office and Procurator Fiscal Service, n.d.). Complying with the disclosure regulation also enhances the credibility and public confidence of the expert witness.

Essentially the disclosure test requires the following four points to be maintained:

- **Retain** all physical, written and electronic information
- **Record** all work and findings in relation to the investigation, from the receiving of instructions to the end of the case.
- **Reveal** all relevant material to the Crown
- **Review** conclusion if new information comes to light.

(Crown Office and Procurator Fiscal Service, n.d.)

A fundamental and distinctive aspect of Scot’s criminal law states that there must be at least two sources of independent evidence to support a proposition, before the defendant can be convicted. The law of corroboration was regarded as a safeguard against convictions based on dishonest or mistaken witness evidence; however, in cases where evidence is minimal, this can result in a poor prosecution case. Sexual crimes, usually committed in private, with only the offender and the victim present is a prime example of cases where corroboration can be difficult to obtain (The Scottish Government, 2012).

Although documents are available regarding the conduct of an expert witness in Scotland and the professional relationship that must be upheld, little documentation is available regarding the guidelines for admission of the evidence and the expert. This lack of guidance and scrutiny has led to several cases of appeal, based on expert evidence.

McCreight v HMA HCJAC 69 [2009]

In the case of McCreight v HMA, an appeal to a murder conviction was granted on the grounds that fresh evidence was available, and there were flaws discovered in the forensic investigation including, the testing of the body samples, which were found to be incomplete. On theses grounds of flawed forensic procedure the conviction was quashed (McCreight v HMA HCJAC 69, 2009).

The Fingerprint Inquiry, Scotland

The fingerprint inquiry was established after a murder case highlighted fundamental flaws in fingerprint examination. During the investigation, a fingerprint allegedly belonging to a police officer was found on a doorframe within the house of the murdered victim, despite the fact that the investigation team had been instructed to not enter the premises.

During the trial, the police officer testified to the fact that the fingerprint on the doorframe was not hers; despite this, she was prosecuted for perjury. The police officer was later acquitted by the jury, based on evidence from two independent fingerprint experts (Campbell, 2011).

This led to an inquiry into the Scottish Criminal Record Office (SCRO), who were responsible for analysing the fingerprints. It was found that in its current state, the SCRO were ‘unable to provide a fully efficient and effective service’.

Due to this admission, the individual convicted of the murder appealed his conviction, as fingerprint evidence had played key role in his conviction. Upon appeal the conviction was quashed (Campbell, 2011).

A parliamentary inquiry found that highly experienced experts had vastly different professional opinions on the degree of similarity between the two fingerprints, exposing weaknesses in the fingerprint examination methodology; an astounding admission for a well-established and trusted form of forensic evidence (Cromwell, 2011). From the conclusions of this inquiry it was recommended that fingerprint evidence be considered as opinion evidence and not fact.

In a similar case, in England, R v Smith, fingerprint examiners disagreed on outcome of fingerprint evidence, where the appellant appealed a murder charge, in relation to fingerprint evidence resulting in the exposure of flaws in this evidence, which ultimately led to the conviction being quashed.

The Scottish Universities Insight Institute Report, 2011

In 2011 the Scottish Universities Insight Institute (SUII) funded a series of workshops to examine the risks involved in using evidence from science and technology in Scottish criminal trials and to identify appropriate protocols to regulate the admissibility of scientific evidence in Scottish courts.

From the discussions held at these workshops, attended by scientists, lawyers and statisticians, it was recommended that the courts should adopt a ‘gatekeeping’ role to ensure only robust scientific evidence is used in criminal proceedings, and that criminal procedure rules, similar to those in England and Wales should be enacted in Scotland. It was also recommended that forensic methods and techniques should be validated by the peer review process, and that there is a need for non-scientist members of the proceedings (i.e. lawyers) to have an understanding of scientific methodology and statistical analysis. Moreover, the codes of practice that are being developed by the Forensic Science Regulator should be considered for implementation in Scotland (Scottish Universities Insight Institute, 2011). Despite these recommendations, no formal appraisal has been conducted by the government in Scotland, and as such, flaws in the admission of expert evidence still exist in Scottish criminal courts.

Hainey v HMA CJAC 47 [2013]

In the case of Hainey v HMA a murder conviction was appealed on the grounds that there was an absence of proper direction or misdirection by the trial judge. During the trail, the focus, from both sides was on whether the cause of the child's death could be established through the use of expert evidence. The Crown's case was essentially of murder, caused by the appellant having failed in the proper care of her child.

A post-mortem examination failed to determine a cause of death because the body was too advanced in decomposition. The cause of death was therefore deemed as 'unascertained', as both natural and unnatural causes could not be excluded or confirmed. Upon the cause of death being unascertained, the Crown sought to support the conviction of murder by relying on evidence to support 'cortical erosion' and 'Harris lines', both which may indicate pre-death stress, arising from neglect and malnutrition, which arguably led to the child's death.

Much of the appellants appeal was based on an attack on the evidence provided by experts, as well as the judges direction relating to this evidence, as it was stated that the two witnesses did not have the necessary level of expertise, their evidence fell below the standards required by an expert witness and their evidence was not corroborated, and should therefore be disregarded. Despite this, the trial judge rejected the plea from the defence counsel to disregard this evidence, stating that, the function of a trial is to examine and test the evidence from each side and that it was the matter of the jury to decide the weight of evidence. At this point it was highlighted by the counsel the issue of a lack of 'gatekeeper' role in Scottish criminal trial procedure, which would enable an expert's qualifications and experience to be scrutinised before the trial, and any evidence not meeting the desired criteria could be excluded.

It was later submitted that the trial judge should have advised the jury to disregard the evidence relating to cortical erosion and Harris lines; instead he instructed them to consider what weight, if any, they should place on it.

It was concluded that the misdirection by the trial judge had resulted in a miscarriage of justice, and the conviction of murder was subsequently quashed.

Young V HMA SLT 21 [2014]

The case of Young v HMA is an example of expert evidence being admitted when there was a lack of peer reviewed support for technique.

Case Linkage Analysis (CLA) was used with the aim of finding a common link between multiple crimes, to establish the likelihood that the crimes had been committed by the same person or persons.

CLA was in relative infancy and it was argued that it should be used only as 'decision support' and not provide a definitive answer, and others in the field believe that it is unsuitable for admissions into legal proceedings.

The current error rate was quite high at 25% of cases being incorrectly linked. The underlying statement was that a type of evidence with a high error rate which cannot be explained and only a small number of peer reviewed papers on this method (eighteen since the 1980’s), cannot be admissible.

It was stated that, before CLA could be admissible in court, it must meet some general criteria; must be founded on an agreed set of principle in the scientific community, have generally recognised credentials and have published procedures and protocols.

It was subsequently decided that CLA would not be admissible as evidence in its current state of development (*Young v HMA HCJAC*, 2013).

Summary

It is undeniable that expert evidence has come under fire in recent years, particularly due to miscarriages of justice. Concern has been expressed regarding the capacity of judges and juries to relate to scientific evidence, when they are likely to have little experience in this area. This relates to the fundamental underpinning of the courts and science, having varying objectives and vocabularies which pose challenges to the collaboration between the two (Cromwell, 2011). With the ever growing technologies and advancements in science, justice systems are struggling to keep up with new forms of forensic evidence that are emerging.

Miscarriages of justice represent a small portion of the total number of cases involving questioned expert evidence; however, when these cases arise they have a profound effect by revealing the weakness of the Criminal Justice System to manage this type of evidence.

In Scotland, in particular, there is a need for a review of the law concerning expert evidence and how well the law is meeting the challenges posed by it (Cromwell, 2011). Scotland has yet to consider these issues in a coordinated manner, such as was done in

England and Wales and the U.S. (Fraser *et al.*, 2013; Sinclair, 2013; The Law Commission, 2011).

Fraser *et al.* (2013) produced a paper following a debate at a Forensic Science Society conference in March 2013, where it was concluded that a review of admissibility and presentation of expert evidence in Scotland was needed.

The key challenges relating to expert scientific evidence in adversarial systems were:

- Limited scrutiny to determine whether expert opinion evidence is reliable
- Limited scrutiny to determine whether the expert is reliable
- Cross examining of expert evidence is inadequate due to lack of knowledge and skill of some lawyers
- Absence of a ‘gatekeeper’ (court appointed assessor) means unreliable evidence may be admitted to court.
- Accreditation schemes should exist in all areas of scientific evidence to qualify whether the expert is competent, qualified, experienced and skilled.

The paper went on to suggest four solutions to these problems;

1. Pre-trial hearings
2. Trial judge as a gatekeeper of admissible evidence
3. Enhanced disclosure provisions
4. Witness declaration of compliance

Pre-trial hearings are used in some matters in Scottish law, but more readily so in English law. In *Hainey v HMA CJAC 47 (2013)*, Lord Clarke suggested this is something that should now be considered as normal practice in Scotland; particularly relevant in cases where there is extensive expert evidence. This appears to be cost effective as well as helping to streamline the trial process. In cases where both sides are presenting expert scientific evidence, assessing the evidence pre-trial allows any areas of agreement to be identified, thus enabling the focus during the trial to be on any issues in dispute (Fraser *et al.*, 2013).

The judge is employed as a gatekeeper in America and Canada. In America this is based on the Daubert standard of assessing the expert's qualifications, principles, methodology used, subject to peer review and based on verified criteria with known error rate etc. it is argued that the absence of a gatekeeper is a fundamental flaw in the Scottish legal system (Fraser *et al.*, 2013).

It is for these reasons that any forensic evidence, well establish or newly emerging must be scrutinised continually for their reliability and their appropriateness for application in criminal proceedings. This should continually be borne in mind for forensic experts across the spectrum of the field, in a bid to strive to always uphold the utmost of excellence in expert evidence with the ultimate goal of avoiding miscarriages of justice.

The issues discussed have highlighted the need for emerging forensic techniques to ensure reliability and validity of methods has been tested and scrutinised, which will form the basis for this research. All studies were conducted with the central aim of establishing statistical support for methods used to identify individuals from photographic images. This began by acquiring a large database of images of the dorsum of the hand, for the purposes of conducting subsequent analysis.

5 MATERIALS AND METHODS: ‘VEIN PATTERN PROJECT’ DATABASE

This chapter details the recruitment of participants and acquisition of images for the ‘Vein Pattern Project’ (VPP) database. This database comprises digital images of the dorsal surface of the hand, along with selected additional information for 53 participants.

5.1 Participant Recruitment

Participants were recruited from four groups of individuals. After expressing an interest in participation, individuals were provided with information, a questionnaire and a consent form (Appendix A).

The information document outlined what was expected of participants should they choose to commit to the study. This included details of any perceivable risks to facilitate an informed decision regarding willingness and suitability to participate. Individuals were also provided with contact details for the principal investigator and primary academic supervisor, should they have any questions or concerns relating to the project.

The first cohort was recruited from the staff and postgraduate students within the College of Life Sciences, University of Dundee, by email advertisement (Appendix B). Individuals could choose not to participate by disregarding the email. Individuals that expressed further interest were provided with the necessary information. Upon completion of the consent form, participants were allocated an imaging session.

The second cohort was recruited from the undergraduate and Master’s, science, medical and dental students at the University of Dundee. A short presentation was given to these students to provide an overview of the project and to invite them to take part in the study. Individuals that expressed an interest were then invited to attend an imaging session where they would be provided with further information.

The third cohort comprised interested members of the public in attendance at the University of Dundee's Open Doors Day 2012. This is an annual event held by the College of Life Sciences that welcomes members of the public into the college to attend laboratory tours and exhibitions. During this event, members of the public that visited the Centre for Anatomy Human Identification (CAHId) were invited to take part in this research (Appendix B). Individuals who expressed an interest to participate were then invited to attend an imaging session where they were provided with participant information.

The fourth cohort comprised individuals that were in attendance at the 2012 winter meeting of the British Association for Human Identification (BAHId). Conference delegates were invited to take part in the research by attending a 'drop-in' imaging session. Individuals who expressed an interest to participate, by visiting the allocated imaging room, were provided with further information.

All cohorts were instructed to consider the information provided in the participant pack and were given the opportunity to ask questions to ensure they were entirely satisfied with the expectations of their role as a participant. Only when the participant had fully understood what was required of them could informed consent be granted and for enrolment into the study.

Ethical considerations

All data was collected after submission and subsequent approval of a University Research Ethics Council (UREC) application (UREC code 12090) (Appendix C).

The only perceivable risk in participating in this study concerned the measurement of body fat percentage. The chosen method for recording body fat percentage was bioelectrical impedance analysis (BIA); this was measured with a set of BIA capable weighing scales. According to the manufacturer's guidelines, individuals fitted with a heart pace maker should not use the scales and this information was explicitly stated in the participant information and reiterated at the imaging session. Potential participants were required to declare any electrical medical implanted devices including pace maker, on the participant questionnaire.

All other methods used in this study presented no associated health risks. No flash photography was used.

The inclusion criteria for this study stated that participants must be aged 18 years or over and that they had completed and returned the questionnaire and signed consent form.

The exclusion criteria, as detailed above, stated that individuals fitted with a heart pacemaker would be excluded from the BIA section of participation, but could still take part safely in all other aspects of the data collection process if they wished.

Individuals were informed that they could withdraw consent from the study at any point, without justification or explanation.

Protection of privacy, anonymity and confidentiality

On completion of the questionnaire and consent form, participants were assigned a unique reference number (URN) to provide anonymity throughout the study. This unique number was specified on the participant's completed questionnaire and consent form. All consent forms and questionnaires were stored in a secure filing cabinet on university premises and the information contained within them was transferred to, and stored in, an electronic, password access controlled database.

Access to and storage of the data complies with the regulations of the Data Protection Act 1998. Access to participant personal information was restricted to the author only under password access control. Other information held on the database was restricted by the author and shared with supervisors; Professor S. Black and Dr H. Meadows, both within the University of Dundee.

The information pack states that information from the data may be published, but no identifiable or confidential information will be published in association with this research.

5.2 Image and personal data acquisition

Personal details required during the imaging session (sex and age) were transferred onto a recording sheet from the questionnaire.

All participants had the same series of images and measurements taken (except where consent was not given). This consisted of twelve photographic images of each hand, their height, weight and body fat percentage.

Imaging and data acquisition was carried out in one session that took a maximum of ten minutes per individual. To identify the individual from the images (to the author only) during later stages of the project, a label was placed in the field of view, detailing the initials of the author, the database where the resulting images would be stored, the date and the URN for the participant (Table 5-1)

Table 5-1 Label details

	Authors initials	Database acronym	Date in 6 figure format	3 digit URN
Details	Harriet Stratton	Vein Pattern Project	DDMMYY	XXX
Example	*HS*	*VPP*	*100413*	*001*

Images were collected in a room chosen for its convenient location for participants and to minimise disturbance to others in the department. The lighting was optimal, with minimal incoming natural light to avoid shadow. Where it was necessary to collect images at a different location (for the different cohorts) conditions were kept as consistent as possible. However, due to unavoidable circumstances, slight variations in the light levels may have occurred due to variation in ambient and natural light sources.

The method for image acquisition was based on the method developed by Meadows (2011) and Berry (2008). The method utilised by Berry (2008) was adopted from Jain *et al.* (1999) and was further adapted for this study.

All image capture took place around a central base unit to which all imaging equipment was attached (Figure 5.1).

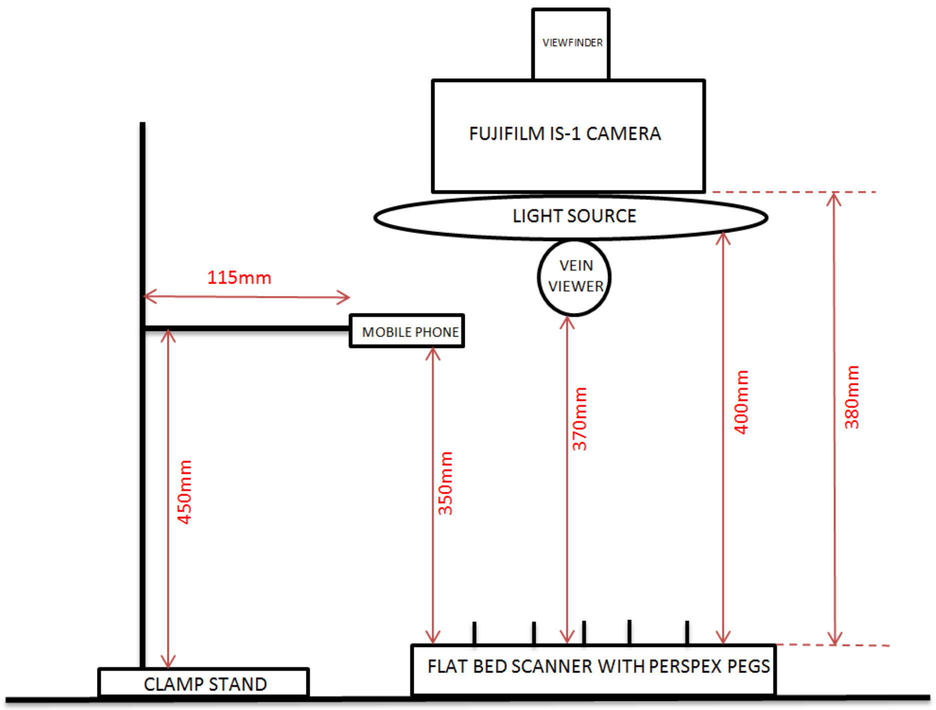


Figure 5.1 Schematic of camera set up

Images were collected in visible light using two different cameras (chosen for their range of resolution) (Table 5-2). Images taken at 5 mp were later excluded, as these were deemed superfluous to the examination of 'highest' and 'lowest' quality parameter, for the purposes of this research.

Table 5-2 Summary of image collection.mp; megapixels.

Imaging equipment	**Resolution (mp)**
Fujifilm IS-1 camera	9

	5
	0.3
Blackberry bold 9700 camera phone	<0.2

On each imaging modality, the dorsum of the hand (left and right hands) was photographed in three positions; the fingers extended, the hand in a clenched fist and the hand held in a semi-pronated position (Figure 5.2).

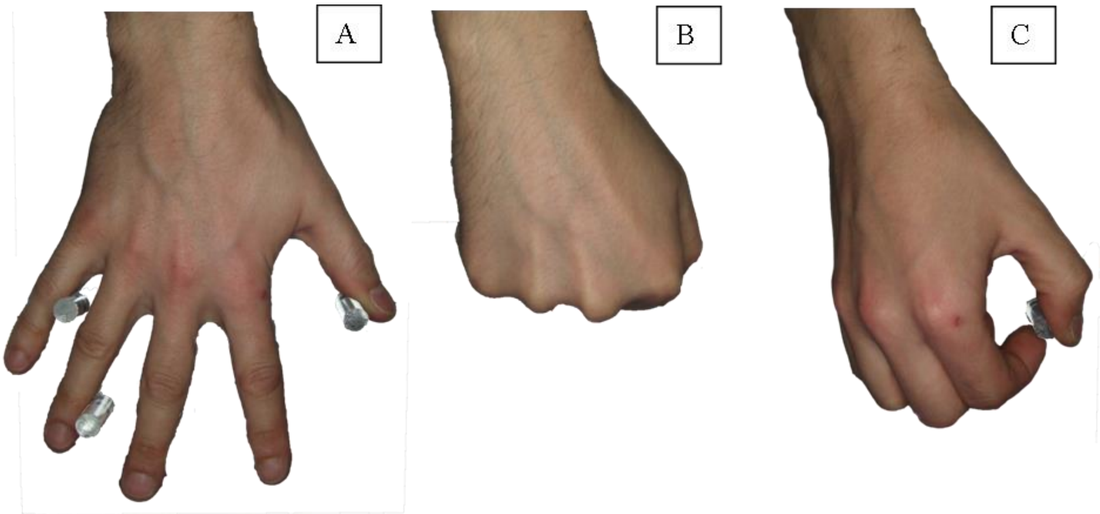


Figure 5.2 Examples images of the hand in three positions; A: fingers extended, B: clenched fist, C: semi-pronated.

The 'fingers extended' and 'clenched fist' positions were chosen to represent a standardised image, showing the full view of the dorsum of the hand. The clenched position was suggested by Bellini (2010) as it provided more reliable information by minimising tendon shadow. The semi-pronated position was chosen to assess if, and how much, vein pattern and surface anatomy information was lost when an image was not standardised, thus representing a forensic case image.

All images were captured with the participants hand (palm facing down) placed on a flatbed document scanner adapted with Perspex pegs as hand positioning aids. The flatbed scanner also contained scale tape around the border to act as further positioning aids (Figure 5.3).

Figure 5.3 Flatbed scanner used as positioning aid for participants' hands.

Participants were asked to place their right hand first, followed by the left hand on the flat-bed scanner whilst the images were captured (participants changed the position of their hand as directed by the author).

Due to the constraints of the equipment set up, the flatbed scanner was moved during the imaging session to accommodate the acquisition of images from the different imaging modalities. To ensure continuity across the database, guide lines were marked onto the base unit to ensure position changes were consistent between participants (Figure 5.4).

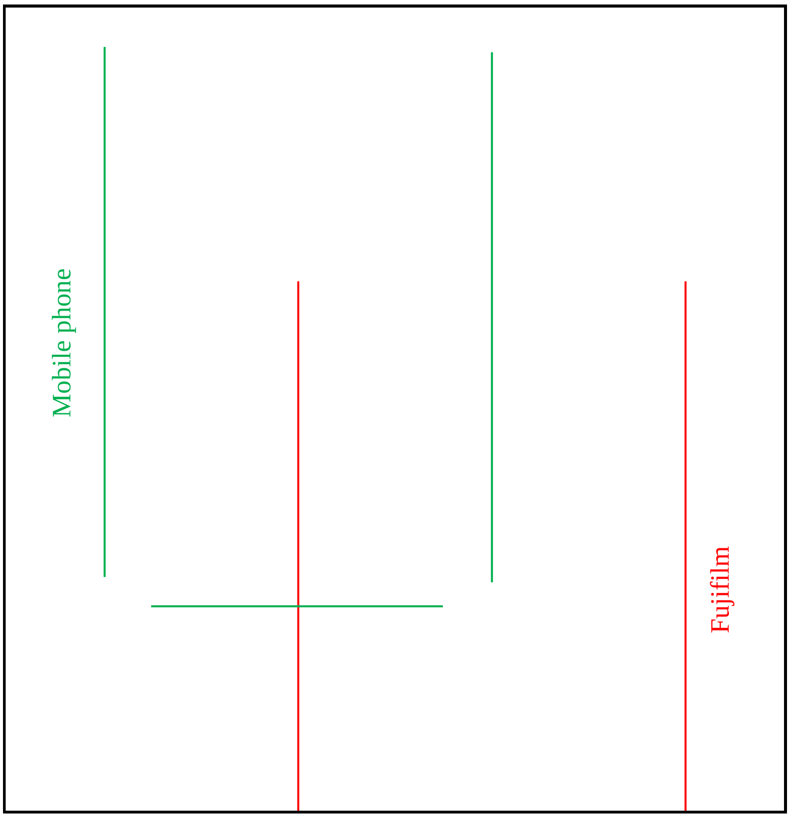


Figure 5.4 Guidelines used as aids for the positioning of the flatbed scanner between imaging modalities.

Visible light images on a Fujifilm IS-1 Digital Camera

A Fujifilm IS-1 digital SLR camera was used to capture visible light images at three settings of resolution. The three settings of resolution were chosen for the largest range (highest, middle and lowest resolution) from a range of available settings. The highest setting of 9 megapixels (mp) (normal) (3488 x 2616 pixels), middle setting at 5 megapixels (2592 x 1944 pixels), and the lowest setting of 0.3 megapixels (640 x 480 pixels) were selected.

The camera was secured to a camera mount on the base unit which was held 380 mm above the subject. A daylight lamp encircled the camera lens, held in position by an angle poise mechanism. This provided a controlled source of even illumination, directed to the subject (Figure 5.1 and Figure 5.5).

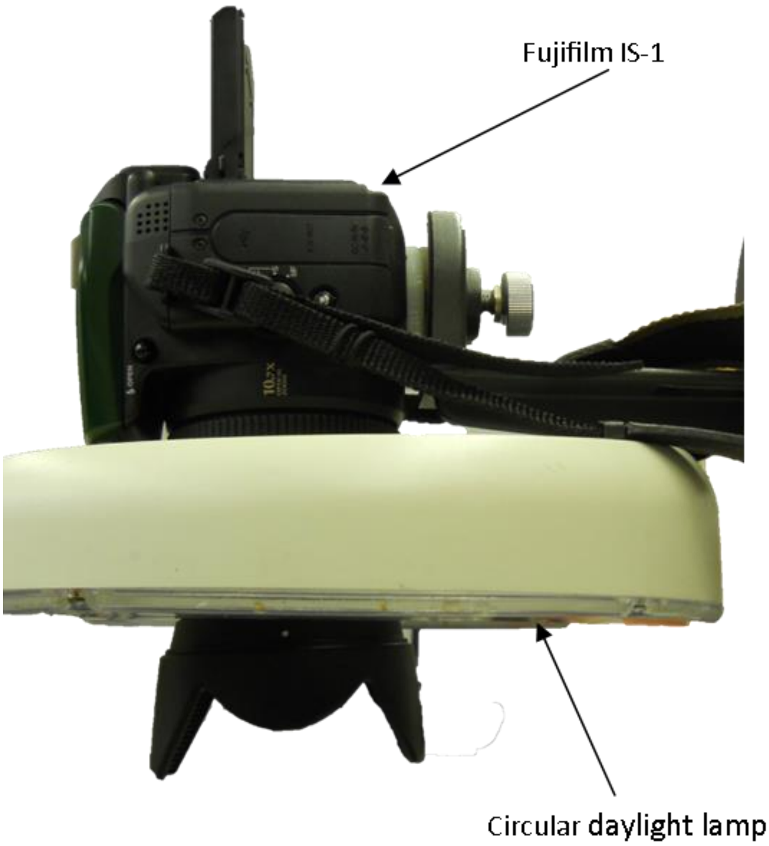


Figure 5.5 Fujifilm IS-1 camera in position with the circular daylight lamp.

For these images, the flatbed scanner was positioned within the red lines on the base unit (Figure 5.4).

For the capturing of all images, the camera was set to ‘P’, ‘programmed auto’; an automatic mode where settings can be adjusted except for the shutter speed and aperture. The auto bracketing mode was selected and set to +/-1EV (exposure value). This captured the same image at three different exposure settings; one correctly exposed, one under exposed and the other over exposed.

The lens was set to 35 mm zoom, and the focus mode selector was switched to ‘C-AF’ (continuous auto focus) setting, which reduced the time required for focussing. When taking an image, the shutter button was pressed to the ‘half-depressed’ position until the green indicator lamp changed from blinking to solid lit, along with a beep to indicate the camera was in focus. The shutter button was then fully depressed until a 'clicking' sound indicated that the image had been captured.

The resolution setting was adjusted manually by the author. This was achieved by pressing the '***F***' button to display the 'Quality mode' menu on the liquid crystal display (LCD) screen. The arrows were then used to navigate to the correct resolution setting, before selecting 'OK'.

Visible light images on a Blackberry Bold 9700 Camera Phone

The camera feature on a Blackberry Bold 9700 mobile telephone was used to capture images in visible light, to represent low quality images in a forensic case image.

The mobile telephone was held in place 350 mm above the flatbed scanner by a clamp stand.

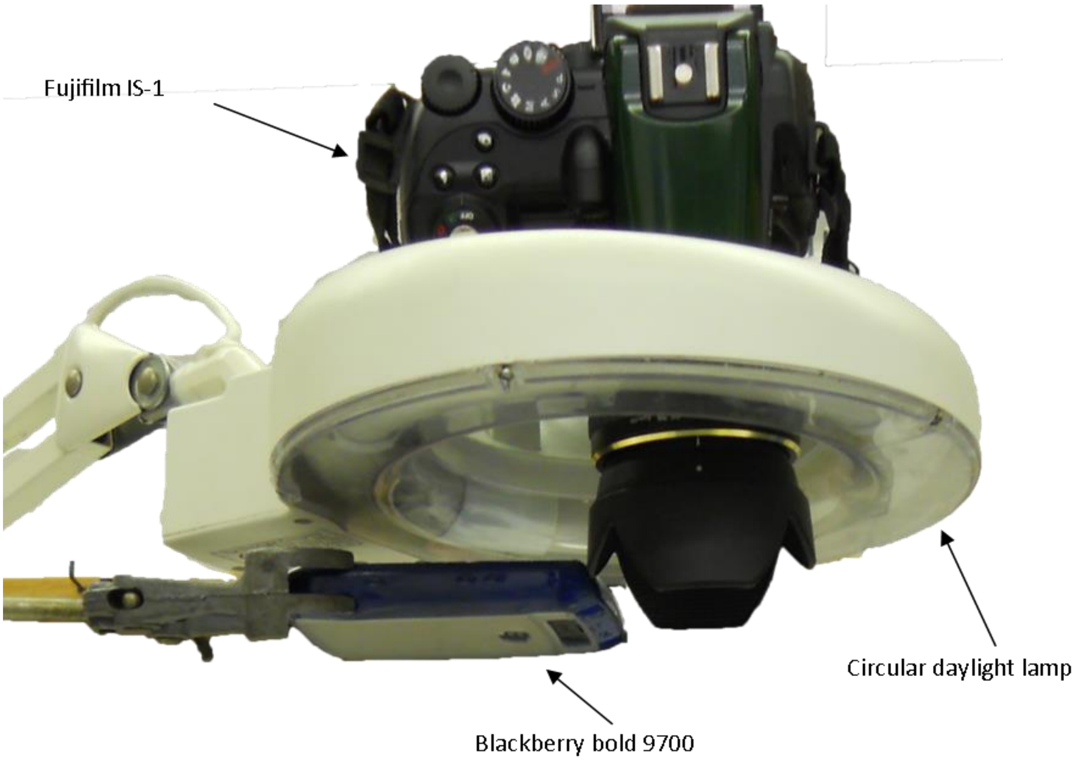


Figure 5.6 Blackberry Bold 9700 mobile phone held in position beneath the circular daylight lamp

The flatbed scanner was moved into position using the green guidelines on the base unit to ensure it was within the field of view of the mobile phone camera (Figure 5.4).

The flash on the camera was turned off, autofocus was set to ‘normal’, white balance was set to ‘automatic’, picture size was set to ‘small (480 x 360 pixels) (<0.2 mp), and picture quality set to ‘normal’. After all settings were adjusted and the hand was in position, the image was captured by depressing the central button on the keypad.

Body Fat Percentage

Where consent was granted, the participant’s body fat percentage (BF %) was measured using BIA technology on a set of specially adapted weighing scales; Tanita® Inner Scan ® V Segmental Body Composition Monitor BC-601.

The scales require some personal information from the user (participant) to accurately record BF%. This information included the height of the individual, measured using a stadiometer. The participant was asked to stand upright, bare foot on a stand-alone height scale, whilst the height indicator was moved to the top of their head. The height was recorded to the nearest centimetre.

On the hand-held console component of the BIA scales, the author selected ‘Guest’. When the dial had settled at ‘0’ on the LCD display, the participant was asked stand on the BIA scales ensuring their bare feet were in contact with the electrodes and holding the hand-electrodes at waist height, until a ‘beep’ sound was heard (Figure 5.7A). This indicated that all measurements had been recorded. When prompted, the participants personal details were entered into the console (age, sex, height and activity level: 1 = no activity, 2 = moderate activity, or 3 = high activity).

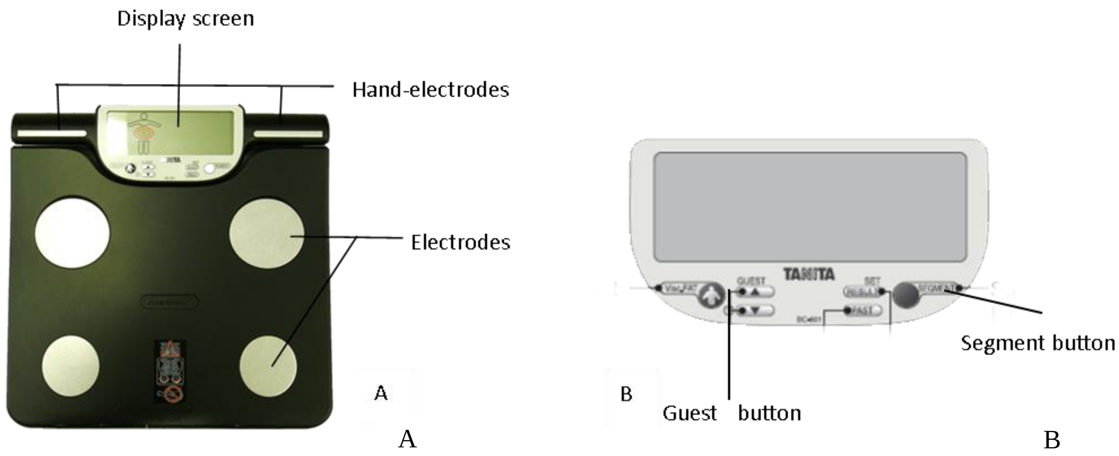


Figure 5.7 Key functions on the BIA scales. A: BIA scales, B: LCD console.

The results appeared on the LCD screen and the relevant results were noted on a recording sheet (weight, BF% total, BF% left upper limb, BF% right upper limb).

To access the body fat percentage for the individual segments of the body the ‘Segment’ button on the handheld console was selected; repeatedly pressing this would navigate through each segment, indicated by the display on the console (Figure 5.7B). The segmental measurements for the left and right upper limbs were also recorded for the purposes of this study.

Data organisation

Upon completion of imaging, all images were archived into anonymised directories within the VPP database. All personal information was transferred into an Excel spread sheet (Appendix D shows information relating to individuals whose data was utilised for this research.).

5.3 Database summary

A total of 178 participants were recruited and enrolled on the Vein Pattern Project (VPP) database (Table 5-3).

Table 5-3 Summary of participant cohorts. BSc; Bachelor of Science, MSc; Masters of Science, BDS; Bachelor of Dental Surgery, MBChB; Bachelor of Medicine.

Cohort number	Cohort	No. participants
1	Staff and students from the College of Life Sciences	41
2	BSc/MSc students	55
	BDS students	39
	MBChB students	17
3	Attendees at the 2012 Open Doors Day	11
4	Attendees at the 2012 winter meeting of BAHId	15
	Total	178

Each individual had 24 images taken of the dorsum of the hand, in a series of positions (Table 5-4).

Table 5-4 Full database content.

Image variables	Conditions	Total number of images
Setting	Fujifilm IS – 1 DSLR: 9 mp Fujifilm IS – 1 DSLR: 5 mp Fujifilm IS – 1 DSLR: 0.3 mp Blackberry Bold 9700	4
Position	Extended fingers Clenched fist Semi-pronated	3
Side	Left Right	2
	Total	**24 images per individual**

This produced a total of 4272 images on the VPP database.

Extraction of working dataset

To optimise the future value of the database, images were collected in excess. Upon completion of data collection aspects relevant to this research were extracted.

Individuals who exhibited characteristics of the most common physical ‘profile’ of a child sex offender, based on knowledge from forensic case work carried out in CAHId, were extracted; Caucasian, male, and between 18 and 40 years of age.

Images taken at the two extremes of the range of resolution from the Fujifilm camera were selected; the highest (9 mp), and the lowest (0.3 mp) resolution images for comparison of ‘highest quality’ and the ‘lowest quality’ images, as well as the mobile phone images for relevancy to forensic case images.

Two hand positions were selected. The ‘clenched fist’ position was chosen due to its presence in the literature relating to photographic imaging of the dorsum of the hand for biometric purposes (Prathyusha and Kumar, 2009; Tanaka and Kubo, 2004; Zhao *et al*., 2007). The ‘semi-pronated’ hand pose was chosen to mimic the ‘non-ideal’ pose, analogous to a forensic case image. This provided images which could be used for comparison between standardised circumstances (‘clenched fist’ images) and a non-ideal hand position (semi-pronated).

Final database summary

The refined database contained 12 images for each of the 53 individuals (all male, aged 18 to 39 years). Images comprised the dorsum of the hand in two hand positions (clenched fist and semi-pronated), from both hands (left and right), captured at two levels of resolution on the Fujifilm IS- 1 DLSR camera (9 mp and 0.3 mp) and on a Blackberry Bold 9700 (Table 5-5).

Table 5-5 Reduced database content

Image variables	**Conditions**	**Total number of images**
Setting	High: Fujifilm 9 mp Medium: Fujifilm 0.3 mp Low: Blackberry Bold 9700	3
Position	Clenched fist Semi-pronated	2
Side	Left Right	2
	Total	**12 images per individual**

6 SUPERFICIAL VEIN PATTERN ANALYSIS

This chapter presents the results relating to the assessment of the superficial vein patterns on the dorsum of the hand, commencing with a description of the methodology used to extract vein pattern information to enable quantification. The chapter will then proceed to the observer reliability studies concerning vein pattern extraction. Results will then be presented with regard to pattern variability across the sample population, and how the visibility of the vein pattern may be affected when attempting to extract vein pattern information from images of reduced quality.

The aims of the vein pattern study were:

1) To determine the reliability and repeatability when extracting vein pattern information for subsequent analysis [intra and inter-observer studies].
2) To determine the extent of variation of vein pattern components across the sample population.
3) To investigate the influence of biological characteristics on visible vein pattern.
4) To investigate the robusticity of vein patterns when assessed in an image of poor quality (representative of an offender image), compared to a standardised image (representative of a custodial suite or suspect image).

6.1 Materials and methods

6.1.1 Description of the images

Six hundred and thirty six digital images were extracted from the Vein Pattern Project (VPP) database (Table 5-5).

Images were recorded at three levels of quality;

- Fujifilm IS-1 digital camera at 9 megapixels (mp) (high),
- Fujifilm IS-1 digital camera at 0.3 mp (medium),
- Blackberry Bold 9700 camera phone at <0.2 mp (low).

Images comprised the dorsum of the hand, in two positions from both the left and right hands of participants;

- clenched fist
- semi-pronated

6.1.2 Data extraction

Due to the nature of the images (visible light) and subsequent low contrast, it was not possible to extract the vein pattern automatically with a high level of confidence. Instead, the vein pattern was manually extracted and presented in a format which could be processed by computer software for statistical examination. The vein pattern was manually traced in Adobe® Photoshop® CS5.1 (version 12.1), feature information was then recorded and labelled in a systematic format which could be processed by the data analysis software R© and analysed using network analysis methods.

Stage 1: Manual trace of the vein pattern

Each image file was opened in Adobe® Photoshop®. The background layer was duplicated twice, one renamed as ‘free hand trace’, the other as ‘Linear, directional’. Both layers were auto-contrasted, using the keyboard command ‘Ctrl + Alt + L’. The ‘linear, directional’ layer and the ‘background’ were deselected for the duration of the manual trace. The hue, saturation and levels settings were adjusted to optimise the vein pattern visibility; the values of the adjustments were recorded for each. Using the pencil tool at 3 px size, all visible areas of vein were traced (Figure 6.1).

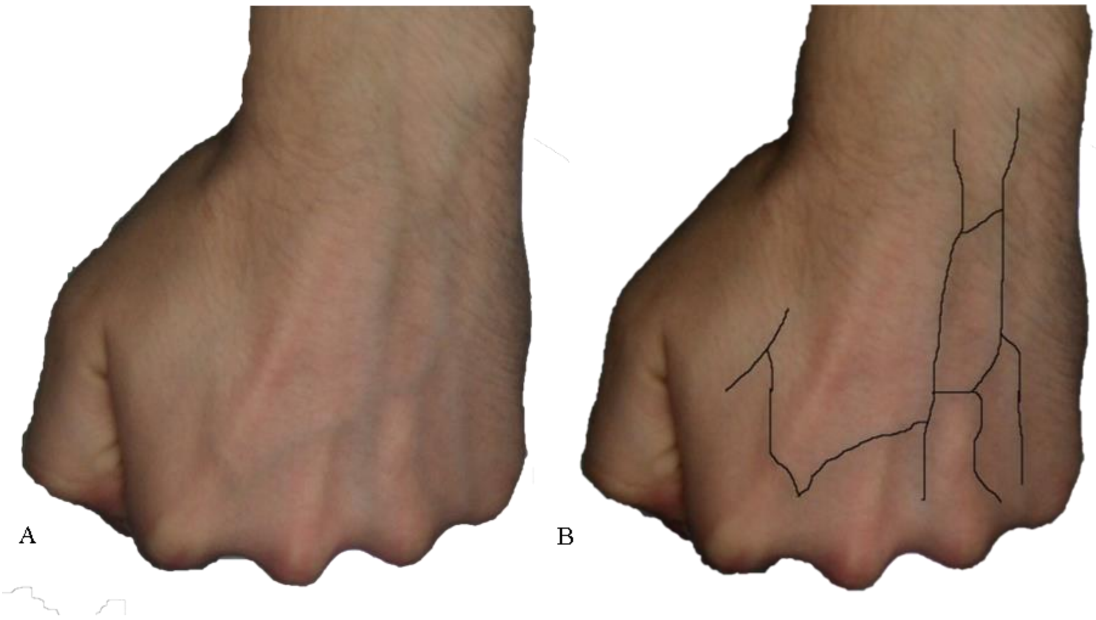


Figure 6.1 A; raw image, B: vein pattern after manual trace.

Stage 2: Production of a linear trace of the vein pattern with directional information

The appearance of the initial vein trace was manually re-traced using the line tool with arrow attachment in Adobe® Photoshop®. This action was performed to remove the curvature or 'normalise' the vein pattern, and to denote the assumed direction of blood flow in the veins (with directionality indicated by the arrow heads). This information was required for aspects of the network analysis computation only.

Normalisation of the vein pattern involved removing any 'curve' information, as the curvature of the vein is dependent on the position and angle of view of the hand. Positional changes were being considered as a variable in this study, and therefore assessing curvature of the veins would have been erroneous as the difference in the degree of curvature could not be accounted for between hand positions.

A curve in the vein would be 'straightened', as long as it did not compromise the pattern details (e.g. a bifurcation point). In Figure 6.2, the curved edge (within the red box) was removed so that the section of vein could be recorded as a single, continuous edge. This was performed by drawing a line as depicted by the dashed line in Figure 6.2.

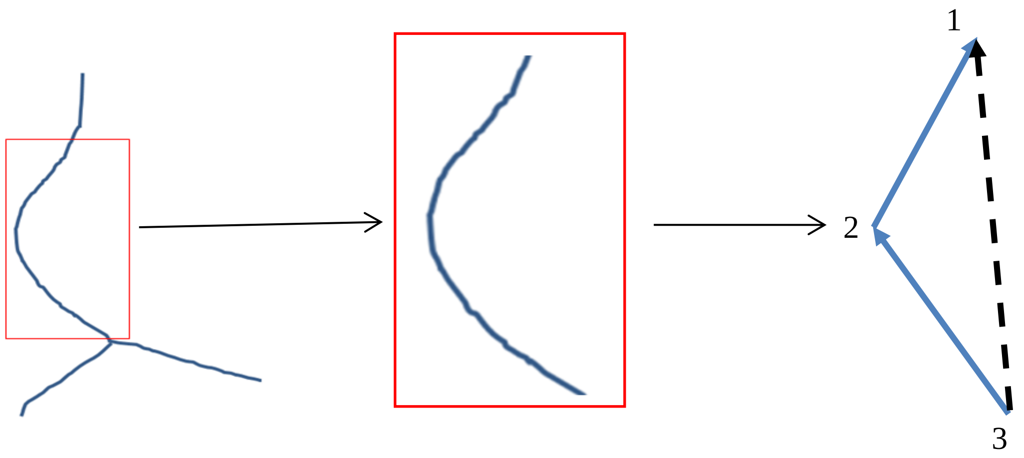


Figure 6.2 Normalisation of a curved line

The ‘Linear, directional’ layer was selected and highlighted, whilst maintaining selection of the ‘Free hand trace’ layer. The opacity was altered to 70% using the slider control in the opacity tab, allowing the original trace to be simultaneously observed via a transparent layer.

The line tool was then selected and set to a weight of 0.1 cm (width to 250%, length to 500% and concavity to 0%), with an arrow selected to appear at the end of the line. The lines with arrows were placed over the original trace to depict the assumed direction of blood flow within the veins i.e. distal to proximal.

Where a region of the vein lay transversely across the dorsum of the hand, the direction of blood flow could not be assumed. In these cases, the area of vein was recorded as having ‘bi-directionality’. In such cases, a double-ended arrow was assigned (Figure 6.3).

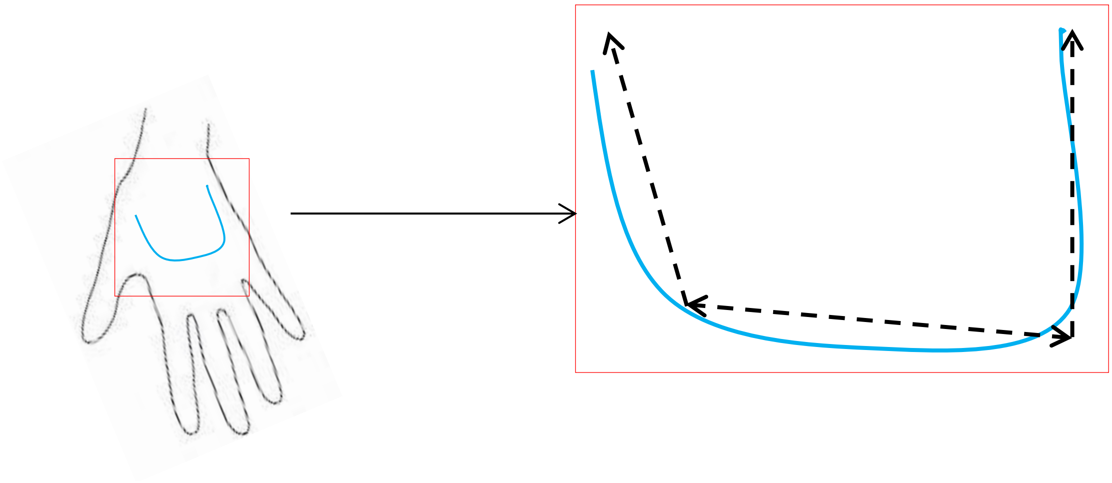


Figure 6.3 Example of a transverse vein arrangement

All lines of the manual trace were normalised until complete.

It should be noted that directional information was used for recording purposes only, to enable the software to compose the networks using numerical information. Data discussed from herein was derived from non-directed networks.

Stage 3: Labelling the features of the vein pattern.

The linear trace layer was isolated from all other layers. Using the ‘Text’ function, numbers were placed, as labels, onto the feature points of the vein pattern. In this context, features consisted of:

- The start point of a visible region of vein
- The end point of a visible region of vein
- A point of bifurcation (e.g. where a section of vein joins another)
- A point of intersection (e.g. where a section of vein crosses another)
- The change of direction of assumed blood flow (e.g. a transverse vein)

These feature points comprised the ‘nodes’ of the resulting vein network.

Once all nodes were numbered, the linear trace and the numbers layers were merged together and saved as a .png file. The original Photoshop file was also saved with all layers for future reference.

Stage 4: Recording vein feature information in R Studio©

A customised R© template file was opened in R Studio©. The image specific details were updated as described in Table 6-1 so that each image type, individual and image setting could be recalled when necessary.

Table 6-1 Specific details required in R template file

Details	**Code**	**Example**
ID	3 digit unique reference number (URN)	001
Side	Left (**L**) or right (**R**)	R
Position	Clenched (**C**) or Semi-pronated (**Sp**)	C
MP	Camera setting; 9 mp (**9**), 0.3 mp (**0.3**), mobile phone (**MP**)	9
User	First initial. Last name	H.Stratton
Date	Date of trace	01/04/2013
Repeat	Repetition number	1

Vein network information was recorded within the template, using the format; source node, target node (Figure 6.4D). The source node was represented by the start point of the edge (the first visible area of vein) and the target node, by the end point of the edge; information which was indicated by the direction of the arrows placed in stage 2. In the case of a bi-directional edge, the edge was recorded twice, accounting for each direction shown by the arrows. The R© file was then saved and stored in the applicable directory with all the other traced images for that individual.

Once the vein pattern was formalised in R©, it was referred to as a ‘network’. When discussing vein patterns after this stage of data extraction, it shall be referred to as a network. Figure summarises all four stages of the methodology.

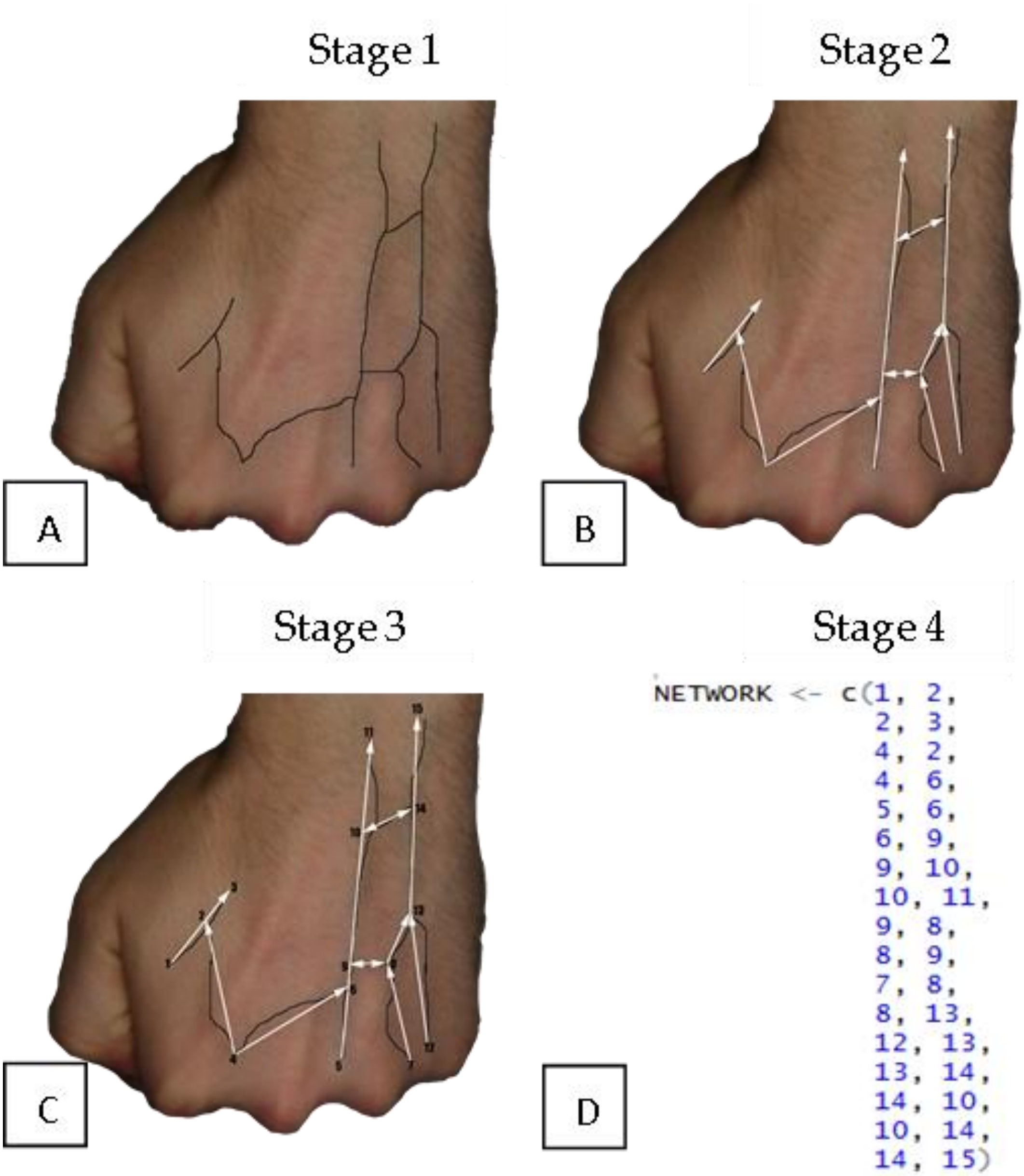


Figure 6.4 Complete process of extracting superficial vein pattern. A: Manual trace complete. B: Linear, directional trace completed, C: Labelled vein pattern, D: Vein network recorded in R Studio©.

6.1.3 Data analysis

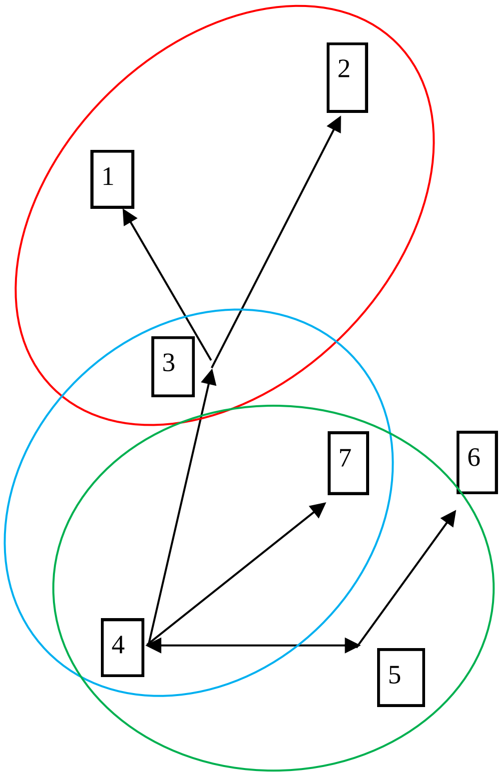
Network analysis was employed to analyse the vein network data; the background to which was discussed in section 4.6. This section will describe the specific methods applied to the analysis of vein network data.

Analysis of the vein network

The software programme R© (version 3.1.1, R Development Core Team, 2014), was utilised for the analysis of the vein network data. R© is a language and environment for statistical computing, data manipulation, numerical analysis and graphical display. It is described as a flexible tool for the development of interactive data analysis. This enables a limitless number of possible statistical tests to be run, tailored to the requirements of the researcher (Venables *et al.*, 2013).

Various R© functions (Appendix E) were coded to 'read' the information from the numerical format of the vein network (Figure 6.4D).

Many of these functions rely on the "graph" package. After a consistency check, R© re-constructed the networks using the numerical information. A specific function then considered all possible 3 and 4 node motifs within a network, accounting for all combinations of nodes and edges (i.e. a node can occur in more than one motif). Figure 6.5 shows examples of some of the motifs within a network and how they can overlap.



3, 1,

3, 2,

4, 3,

4, 7,

4, 5,

5, 4,

5, 6.

Figure 6.5 Example of how a network is labelled and overlapping motifs.

Each motif was represented by a binary matrix indicating how the nodes were connected. Such a matrix was created for all networks to establish node connections and subsequent motifs (Figure 6.6).

Node number	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	0	0	1	0	0	0	0
2	0	0	1	0	0	0	0
3	1	1	0	1	0	0	0
4	0	0	1	0	1	0	1
5	0	0	0	1	0	1	0
6	0	0	0	0	1	0	0
7	0	0	0	1	0	0	0

0 = no connections between nodes

Node 5 is connected to node 4

Node 4 is connected to node 7

Figure 6.6 Example of matrix created from network information, to determine the motifs present. Matrix relates to network in Figure 6.5

This matrix was then converted into a binary number, defined by consecutive horizontal lines, e.g. 001000000100001101000 (first three rows of matrix in Figure 6.6). This number was converted to a decimal number and became a unique code for motifs with this exact topology.

The motifs were arranged in numerical order according to the unique code. An arbitrary number, 1 –n, was then assigned to aid with identification of the motifs during computer processing (Ward, 1963). Using the motif numbers, the frequency of each motif within each network was recorded in a matrix (an example is shown in Table 6-2)

Table 6-2 Example of a matrix using information from several networks (M = motif)

	M1	M2	M3	M4	M_n
Network 1	1	2	1	0	…
Network 2	2	0	1	4	…
Network 3	2	1	2	2	…

The presence and number of different motifs can be used to characterise the network in this format.

Sub-isomorphic analysis

By considering the motifs in a deconstructed manner, sub-isomorphic analysis enables in-depth investigation of motif structure within a network. This is illustrated in Figure 6.7.

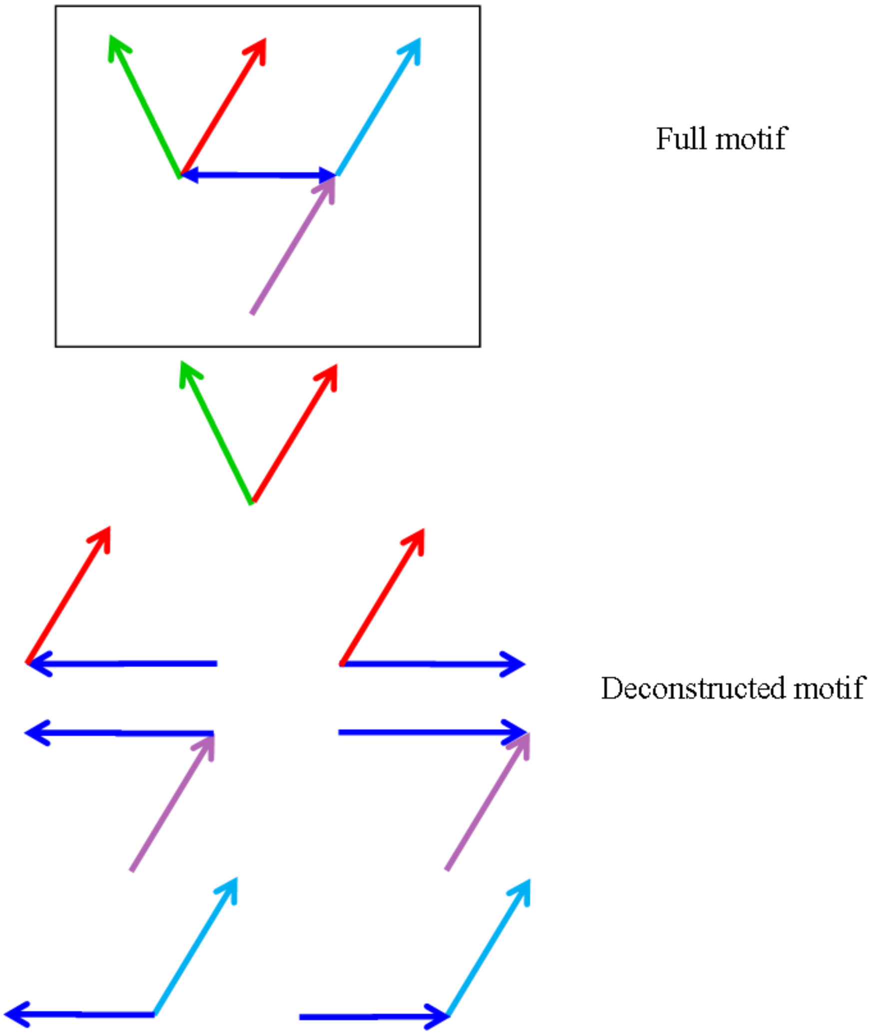


Figure 6.7 Example of deconstructed motifs, as it would be assessed during sub-isomorphic analysis.

Sub-isomorphic analysis breaks down the network into its constituent motifs. Note that a double ended arrow (in cases of transverse veins) is broken down and two motifs are considered. This approach to assessing motifs was important when assessing similarities in the vein network recorded in the observer studies.

6.2 Observer reliability study

This study addresses the validity of the method used to extract the vein pattern. The repeatability of the method was tested within the same observer (HS) in the intra-observer study and the reliability of the result was tested in the inter-observer study by assessing 21 observers with varying levels of experience.

For both the intra and inter-observer studies, 20 images from the extracted dataset were extracted. The images comprised the dorsum of the hand in a clenched fist position, captured with the Fujifilm IS-1 camera, at 9 megapixels. This image type was selected to minimise error from other sources such as hand position and image quality. A manual trace of the visible area of the vein pattern was produced in Adobe® Photoshop® and embedded within the image following the methodology described in section 6.1.2, stage 1 (Figure 6.4).

20 images were selected to display a range of network complexities and were classified as having a dense, intermediate or sparse vein pattern. Classification of the networks was achieved by several modes of assessment. Visually assessing the traces involves a subjective opinion; therefore multiple methods were employed to classify the networks;

- Visual inspection of manual traces of the vein patterns (Trace)
- Visual inspection R© composed networks (Network)
- Number of edges in the network (Edges)
- Number of nodes in the network (Nodes)
- R© generated complexity score (the ratio of number of edges: number of nodes) (Complexity)

The results of each mode of image assessment were recorded for every network. After all scoring was complete the complexity level with the most number of scores was selected as the assigned complexity level for that network (Appendix F).

The final selections were made; 6 sparse networks, 8 intermediate networks and 6 dense networks. More intermediate networks were selected as these types of networks were found to be the most common (Table 8-1).

6.3 Intra-observer repeatability

Intra-observer repeatability informs of the ability for the same result to be achieved on separate occasions, by one observer (the author) and is a measure of consistency (Edmond *et al.*, 2009). Therefore, this study was performed to establish how reliable one observer was in terms of reproducing the network information from a given trace on more than one occasion. The visual differences in the traces were examined as well as quantification of the features observed within the network, from the different repeats. This section commences with the assessment of overall performance, and consequently investigates how network complexity affects observer performance.

6.3.1 Methods

20 images (as detailed in the previous section, with the manual trace embedded) were examined by the author. Stages 2, 3 and 4 of the methodology (section 6.1.2) were completed on six separate occasions, leaving at least 24 hours between sessions to avoid image memory bias. Each repeat was produced in an assigned colour (Table 6-3).

Table 6-3 Colour coding for the six repeats traces in the intra observer study

Repetition number	**Line colour**
1	Red
2	Pink
3	Blue
4	Green
5	Yellow
6	Orange

The linear traces and node labels from each of the six repeats were combined for each network using the layering and merging tools in Adobe® Photoshop®. The resulting

R© files were then used to assess whether the same network was produced on each occasion (Appendix G).

Statistical analysis

A pseudocode version of the R© code used to analyse this data can be found in appendix E.

Specific statistical methods will be described in the relevant section so the methods can be contextualised for clearer understanding.

6.3.2 Results

Overall performance

Visual examination of performance

It was hypothesised that all repetitions of a single network would appear visually similar, due to the fact that an existing manual trace was used as a template. However, it was found that in 70% of the networks, the repeats were dissimilar. This difference was due to a variation in the placement of 1, 2 3 or 4 edges (mostly due to over-normalisation; found in 86% of dissimilar cases). The remaining 14% of dissimilar cases were due to variable placement of edges and nodes.

To illustrate this point, the following images are provided.

Figure 6.8A shows where an edge has not been normalised to the same degree as all other repeats and an extra node has been assigned in the 5th trace (highlighted within the black circle).

Figure 6.8B shows two examples of where edges have been over-normalised in the 2nd trace, compared to other repeats; despite this, the node information did not differ from all other traces.

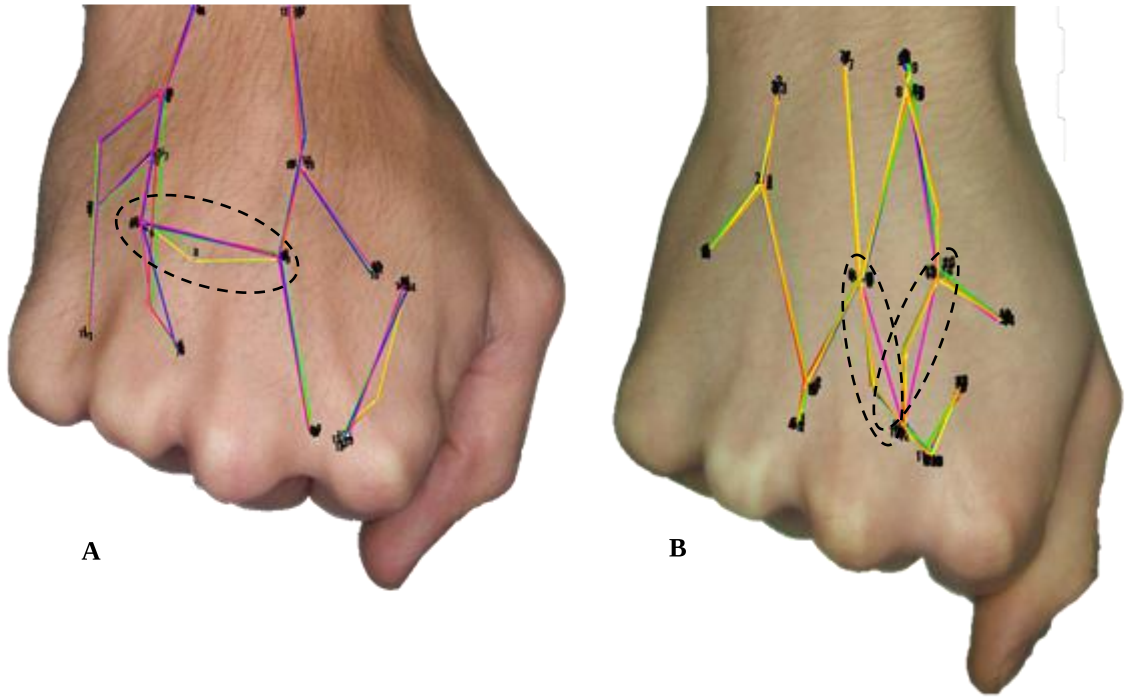


Figure 6.8 Merged traces for networks, A: URN 004 (additional node in the 5th trace (yellow)), and B: URN 163 (over -normalisation in 2nd trace (pink)).

This is important, as a differing placement of a node or nodes will cause a disruption in the resulting network in R©; however, as edge information was not explicitly provided to the software, it was expected that minor variation in the placement of edges would not affect the resulting network.

Assessment of the vein pattern as a network: Pairwise comparison

To assess the overall performance of the intra-observer study, a pairwise comparison matrix was produced. Within this matrix the number of changes (the number of edges that were added to, or subtracted from, a network) required for a pair of repeats to match were recorded. Edge differences were considered in relation to their accompanying nodes (i.e. exact placement, not the number of edges only), therefore enabling all repeats to be compared to one another, whilst considering the topology of the network, rather than feature counts alone. Where the pairwise comparison is equal to 0, this equates to 0 changes required to make the pair match, and therefore the network information was identically recorded in both repeats, termed 'isomorphic' (Table 6-4).

Table 6-4 Example of a pairwise comparison matrix for each network using the number of edges to assess similarities between repeats (data relating to network URN 4).

	Repeats						
		1	**2**	**3**	**4**	**5**	**6**
	1	0	0	1	0	3	0
	2		0	1	0	3	0
	3			0	1	4	1
	4				0	3	0
	5					0	3
Repeats	**6**						0

A total of 15 pairwise comparisons were available for consideration for each network within the matrix. This equates to the 6 repeats, each considered twice, minus the comparison of the same repeat against itself, divided by two, to leave the consideration of each pair once, Equation 6-1).

Equation 6-1 $Total\ pairwise\ comparisons = \frac{(6\ repeats\ x\ 6\ repeats) - 6\ (diagonal)}{2}$

Using this method, the overall performance was examined. From the pairwise comparison matrices for each network, all the cases of 0 (where there were no differences reported between a pair of repeats) were combined to show the overall performance, in terms of repeatability. This is summarised in Figure 6.9, and shown by the percentage of times each network was isomorphic (i.e. equal to 0: no differences between repeats), when considering all the repeats.

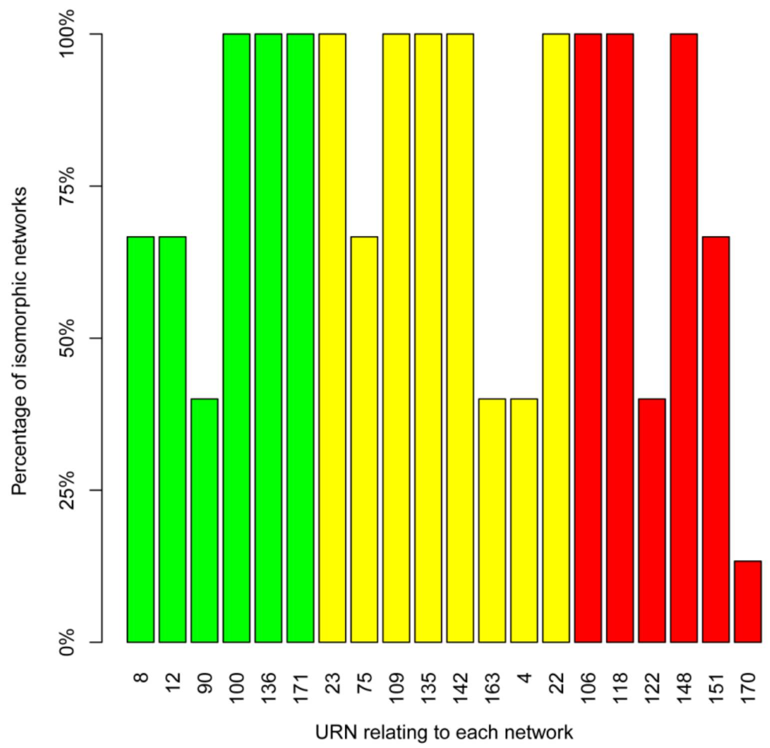


Figure 6.9 Percentage of isomorphic networks from all 8 repeats. Green: sparse networks, yellow: intermediate networks, red: dense networks.

Figure 6.9 shows that 11/21 of the networks were recorded the same in 100% of the repeats. The worst performance was seen in one of the dense networks (URN 170, where only 2 comparisons were isomorphic). Overall the intermediate networks showed the best performance (62.5% of networks were isomorphic in all repeats), followed by the sparse networks (50% of networks were isomorphic in all repeats), with the dense networks showing the worst overall performance in terms of isomorphic networks (also showed 50% of networks were isomorphic in all repeats, however one network showed only 12.5% isomorphic repeats).

Comparison of visual and statistical approaches

The visual and statistical assessment of the observer repeats have been described to demonstrate overall performance. It is important to consider how the two approaches differ to ascertain whether a source of error can be identified; the following networks are considered to illustrate this point.

URN 170 shows several differences in the examination of the traces. The statistical analyses agrees with this, in that the number of isomorphic pairwise comparisons were low (1 isomorphic comparison for repeat 2, 3, 5 and 6, whilst there were no isomorphic comparisons for repeat 2 and 4, meaning all repeats were recored differently. It can be seen that the differences recored ranged from 1 to 4 edge differences (Figure 6.10 A).

URN 135 is an example where visual differences are observed, but when assessed through network analysis, no differences were found (Figure 6.10 B).

URN 12 shows that all repeats were recorded identically from the visual examination, however, when considering the number of pairwise comparisons that were found to be isomorphic, (i.e. 0 differences), only 10 (out of 15) were found. The remaining 5 pairwise comparisons showed a difference of 1 edge. Figure 6.10 C2 shows the breakdown of each repetition for URN 12. Repeat 1, 2, 3, 5 and 6 were recorded the same as 4 other repeats, whereas repeat 4 differed from all other repeats.

Finally, URN 171 is an example of no visual differences observed and no statistical differences found.

This highlights that in some instances the visual trace and statistical approach are comparable, and that in some cases error has occurred in the transmission of data from a ‘well traced’ pattern to the network recording in R.

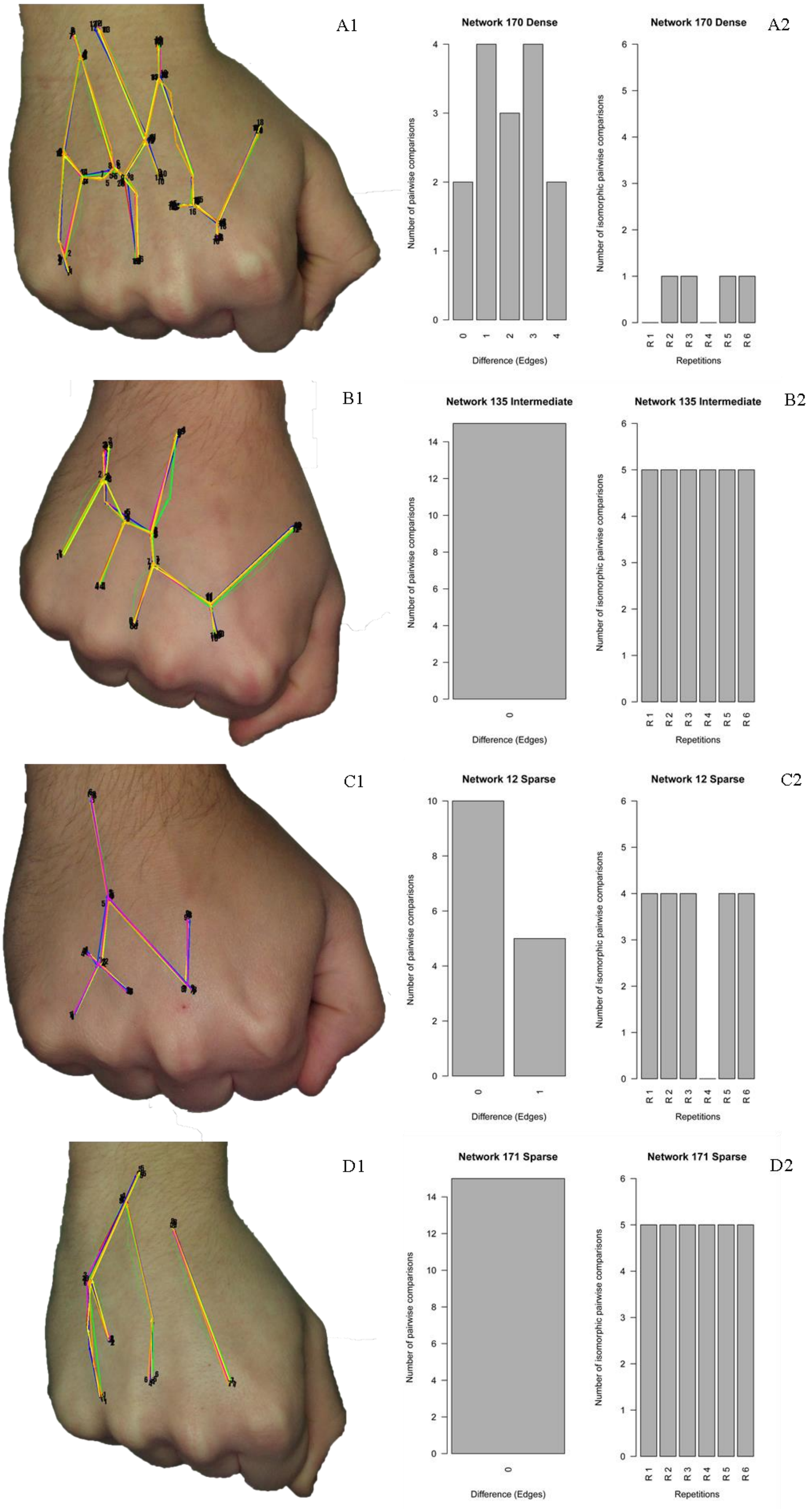


Figure 6.10 Example of the statistical and visual analyses for A: URN 170, B: URN 135, C: URN 12, D: URN 171.

Intra-observer performance regarding motif detection

Motif detection was also utilised to demonstrate observer performance. Pairwise comparisons were employed to assess the number of times the same 3 and 4 node motifs were identified. The number of times a score of 0 was observed in the pairwise comparison matrix gives an indication of how repeatable was each motif.

For each network a matrix was created; illustrated in Table 6-5, where both repeats have identified the correct type of motifs; however, the number of motif 2 differs between the two repeats. Therefore in a pairwise comparison scenario, repeat 1 and 2 are not isomorphic due to this difference in the number of motifs detected. The data from these matrices is summarised in figures Figure 6.11 and Figure 6.12, for the 3 node and 4 node motifs respectively.

Table 6-5 Example of determination of 'motif count'.

	Motif 1	Motif 2	Motif 3
Repeat 1	1	2	4
Repeat 2	1	3	4

The results for both the 3 and 4 node motifs were similar. Motif detection performance was found to be best in the dense networks (66% isomorphic networks), the opposite of what was seen with edge detection.

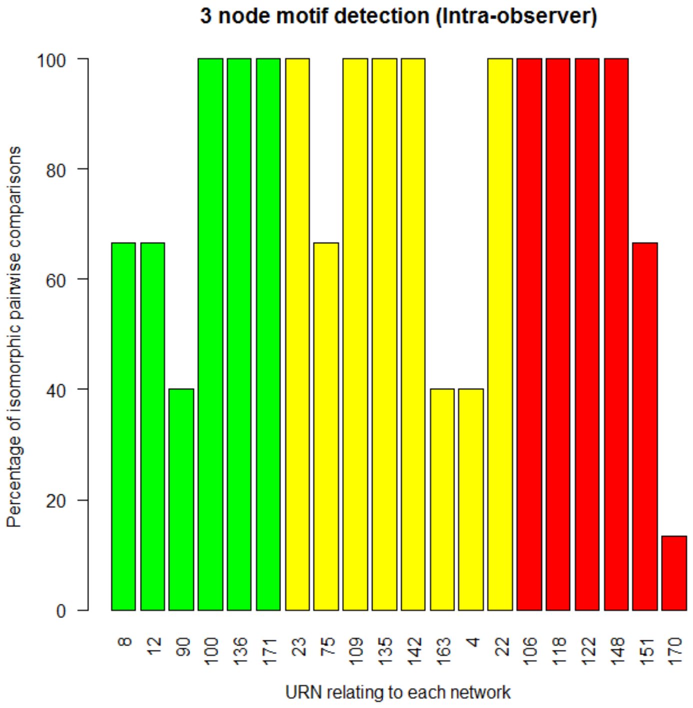


Figure 6.11 Percentage of pairwise comparisons where the same number of 3 node motifs were observed. Green: sparse networks, yellow: intermediate networks, red: dense networks.

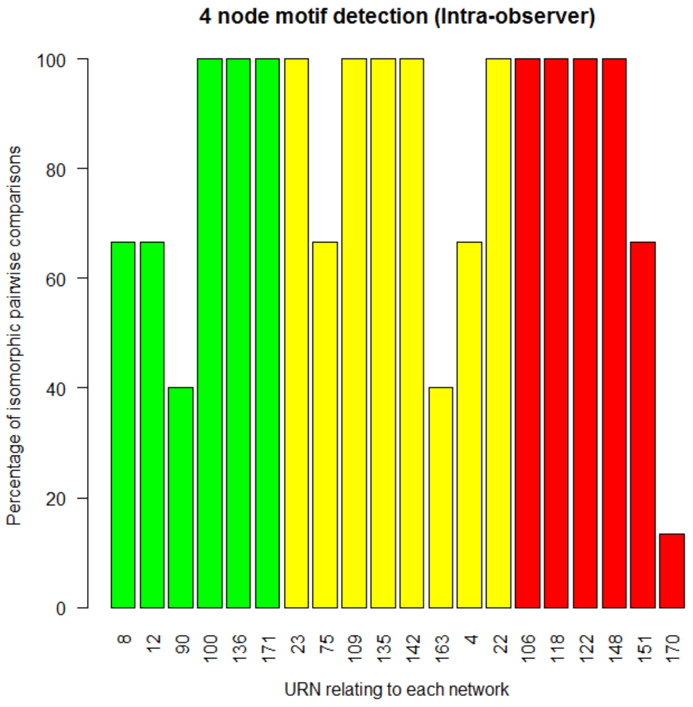


Figure 6.12 Percentage of pairwise comparisons where the same number of 4 node motifs were observed. Green: sparse networks, yellow: intermediate networks, red: dense networks.

Observer performance regarding prominent vein network features

The vein pattern can be examined by its component features; edges, nodes, intersections and loops. Figure 6.13 shows the topology of these two additional features; a loop is an area entirely enclosed by veins, and an intersection is an area where two veins cross each other.

Figure 6.13 Examples of a loop (α) and an intersection (l). (Adapted from Meadows (2011)).

The current research utilised these features in the assessment of vein network repeatability as previous research suggested intersections and loops to be useful features in terms of identification due to their relatively low prevalence in a population (Meadows, 2011).

Intersections

In the intra-observer study, intersections were consistently identified across the dataset regardless of the assigned complexity of the network. Where they were present, they were found to be repeatable in all but one case (URN 8, sparse). They were mostly identified in the dense networks, followed by the sparse, with the intermediate networks having the least intersections present (Figure 6.14)

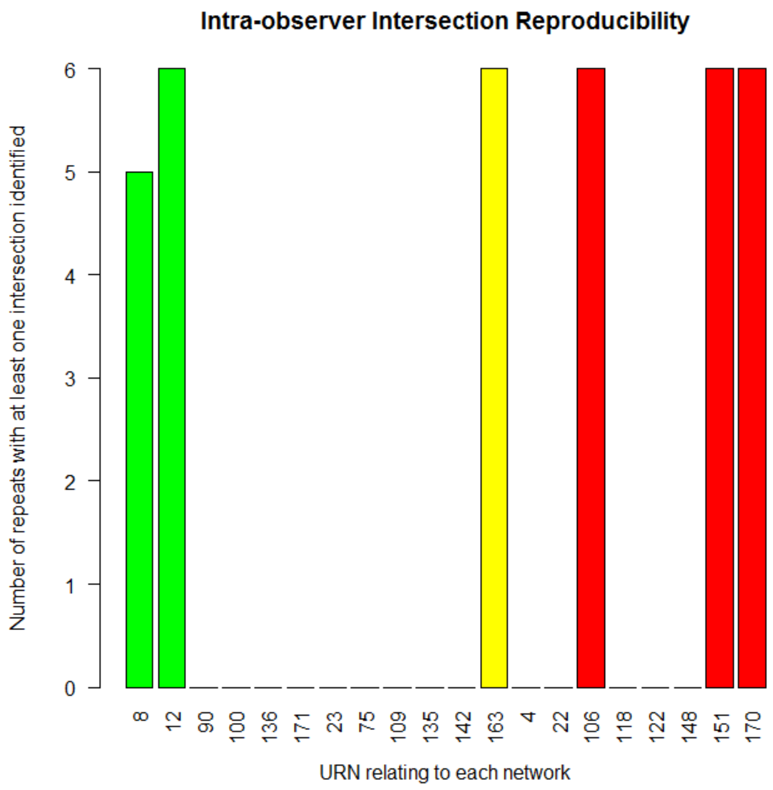


Figure 6.14 Repeatability of identifying an intersection within a network

Loops

Where present, loops were repeatedly identified across the dataset regardless of the assigned complexity of the network, with the exception of 2 networks (URN 8 (sparse) and URN 4 (intermediate). They were mostly identified in the dense networks, where they were identified in all 6 repeats; followed by the intermediate, where 2 out of 3 were identified in all 6 repeats. Loops were identified in only one of the sparse networks which was record in 5 out of 6 of the repeats (Figure 6.15).

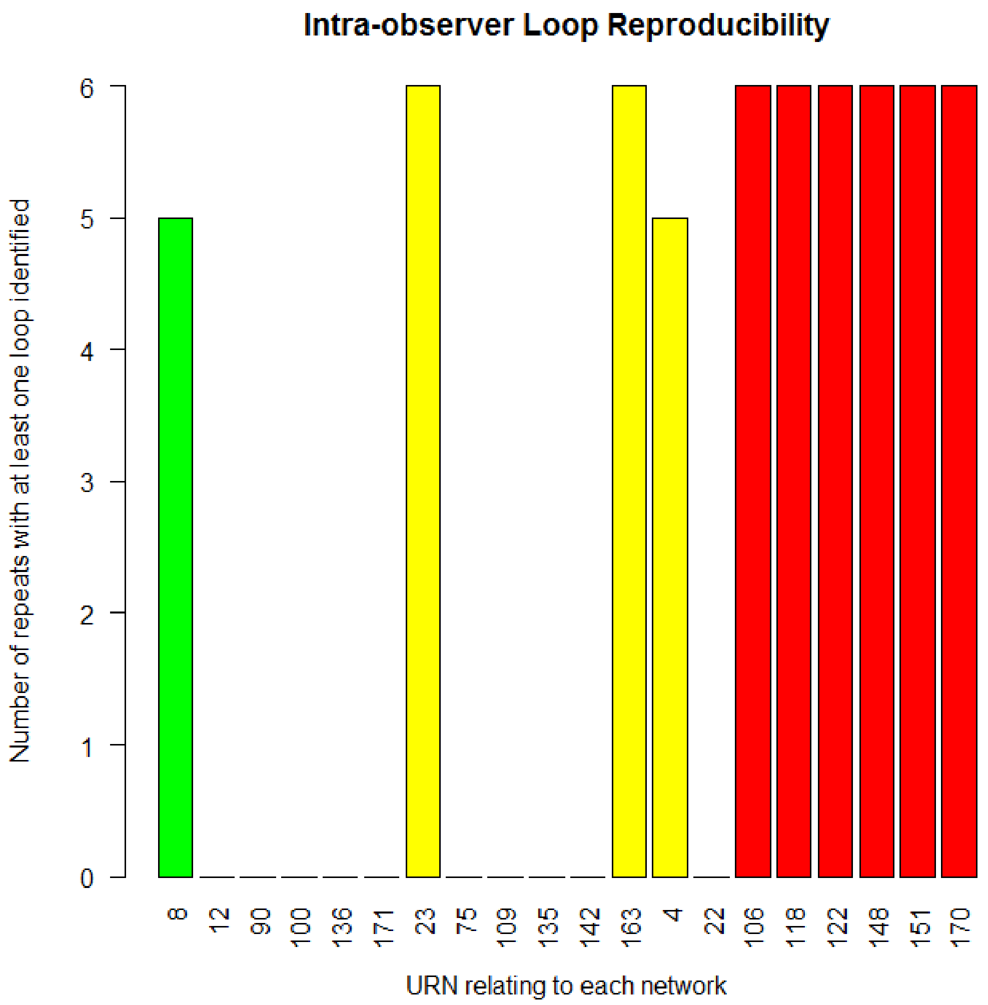


Figure 6.15 Repeatability of identifying a loop within a network

6.4 Inter observer reliability

The inter-observer study was carried out to establish how reliably several observers could reproduce a reference network. Three key aims were addressed during this study, to establish:

- Whether a relationship exists between observer performance and network complexity
- Whether a learning process exists for the extraction of the vein network
- Whether a relationship exists between prior knowledge/experience and observer performance.

6.4.1 Methods

21 observers were recruited through email advertisement within the University of Dundee. Individuals who expressed an interest in taking part were provided with information detailing their involvement in the study, a consent form and questionnaire (Appendix H). Observers were enrolled only after reading, understanding and agreeing to the information contained within the observer pack and by signing the consent form. Upon receipt of consent, observers were assigned a unique reference number for the purpose of anonymity.

Observers were requested to grade their level of experience in four key areas; anatomical knowledge, experience of hand feature analysis, operation of R© software and the operation of Adobe® Photoshop®. For each category individuals were asked to grade their level of experience as; none, minimal, moderate or extensive.

Each observer was provided with 20 images with a manual trace embedded in the image (the same images used in the intra-observer study; section 6.3), along with a set of comprehensive instructions and general operational guidelines for the use of Adobe® Photoshop® and R Studio© (Appendix H). The instructions followed the methods outlined in section 6.1.2, stages 2, 3 and 4 (observer R files in appendix I).

Observers were requested to perform one trace of each of the 20 images in one, 2 – 4 hour period. The study was conducted on the same desktop computer, with an Intuos® 5 Wacom ® graphics tablet and stylus pen. To assess the influence of learning associated with observer performance, observers were instructed to trace the vein networks in one of three sequences;

1) increasing complexity (sparse>intermediate>dense)
2) decreasing complexity (dense>intermediate>sparse)
3) randomly assorted

Network complexity grading and sequence were not disclosed to the observers. The reference network, to which the observer networks were compared, was produced by the author. All analyses were performed using the custom R© code (Appendix E).

The reference network

The reference network was selected at random after testing traces from each of the repeats from the intra-observer study (6 repeats). It was hypothesised that changing the reference network may alter the results from comparison analysis, however little deviation was found, and therefore one reference was selected.

6.4.2 Results

Observer performance and network complexity

To establish the influence of network complexity on the ability of observers to correctly identify features within a network (according to the reference) responses from the observers were assessed on a three tier system:

1. **Identical;** networks are identical[2] to the relative reference network;
2. **Similar;** networks are comparable to the relative reference network, and the removal and/or insertion of up to 4 edges is enough to make them identical[2];
3. **Dissimilar;** networks are quite different from the relative reference network, and the removal and/or insertion of up to 4 edges is not sufficient to make them identical[2].

Using this scale, observers were able to identify 59.52% of the sparse networks as identical. Performance decreased when considering the intermediate (39.88%) and dense (32.54%) networks (Figure 6.16). Observers identified 14.29% of the sparse networks, 30.95% of the intermediate networks and 64.29% of the dense networks as dissimilar. The highest incidence of identical networks was observed in the sparse

[2] Identical in terms of the number of edges.

networks, and the highest incidence of dissimilar networks was found in the dense networks, suggesting that network complexity has a strong influence on the ability to reproduce networks (Table 6-6).

Table 6-6 Percentage of networks classified as identical, similar or dissimilar.

	Sparse	**Intermediate**	**Dense**
Identical	59.52	39.88	32.54
Similar	26.19	29.17	3.18
Dissimilar	14.29	30.95	64.29

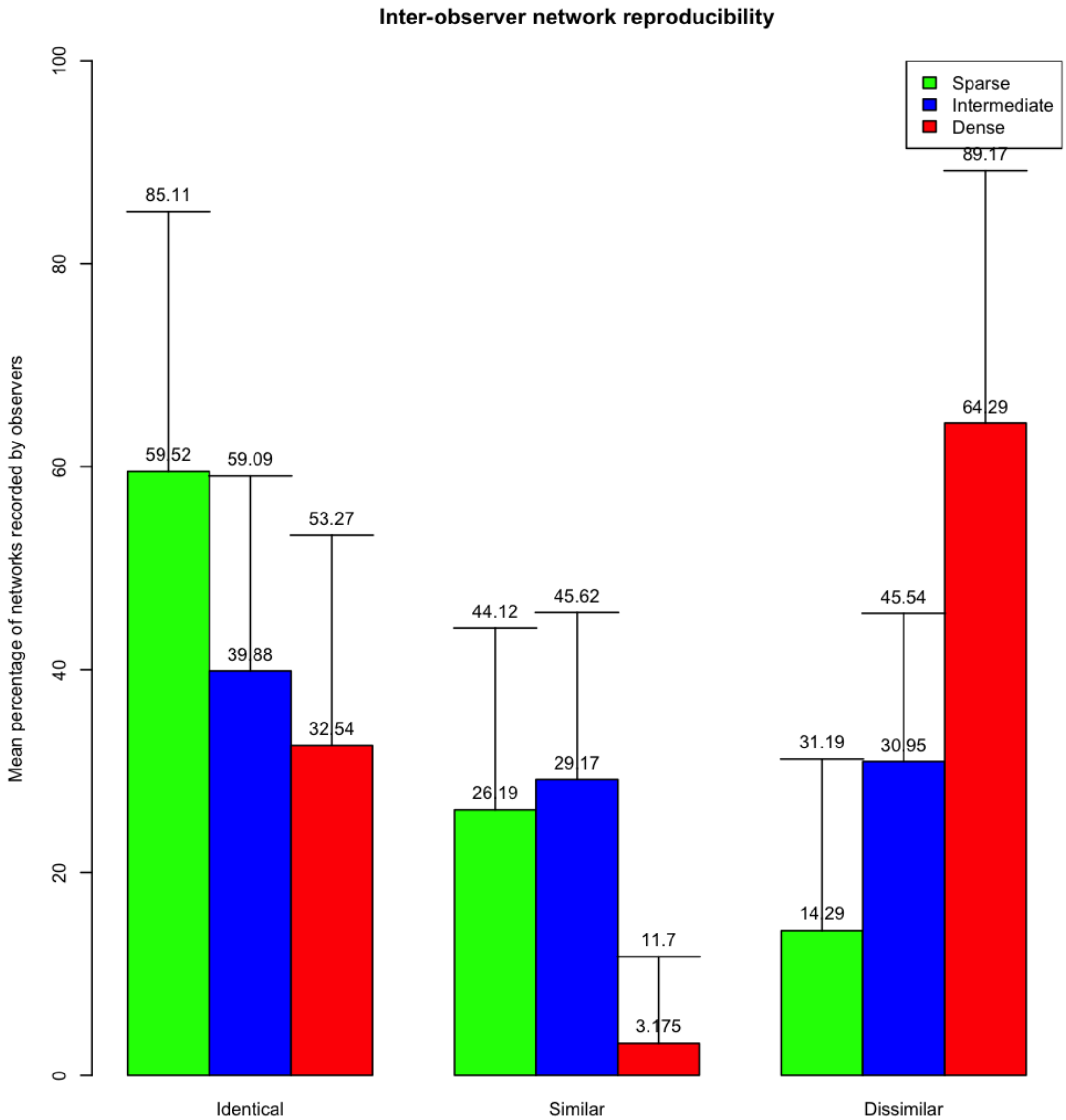


Figure 6.16 Reproducibility of networks according to network complexity. Bars show the mean percentage across all observers, for each observer category (identical, similar and dissimilar).

Influence of learning on observer performance

The observers recruited for this study had no prior experience of applying the techniques investigated in this study, and therefore it was expected there may be an indication of learning during the course of the observer trial.

To minimise error from the complexity of the networks, observers were provided with the images in one of three sequences; increasing complexity, decreasing complexity and at random.

Performance at the start of the study was compared to performance at the end, to establish improvement or decline. This was established by assessing the first four, and the final four networks considered by each observer in their given image sequence. Observers were categorised as performing better (more identical networks at end compared to the start), same (comparable performance at the start as at the end) or worse (more identical networks at the start than at the end). The results from this analysis is summarised in Figure 6.17. The dark blue coloured areas represent the number of observers whose performance improved (better), the light blue areas represent the number of observers whose performance was neither improved or reduced (same). Finally the black areas show the number of observers whose performance was worse at the end of the study, compared to the start of the study (worse). The three bars represent the three image groups (varying order of network complexity).

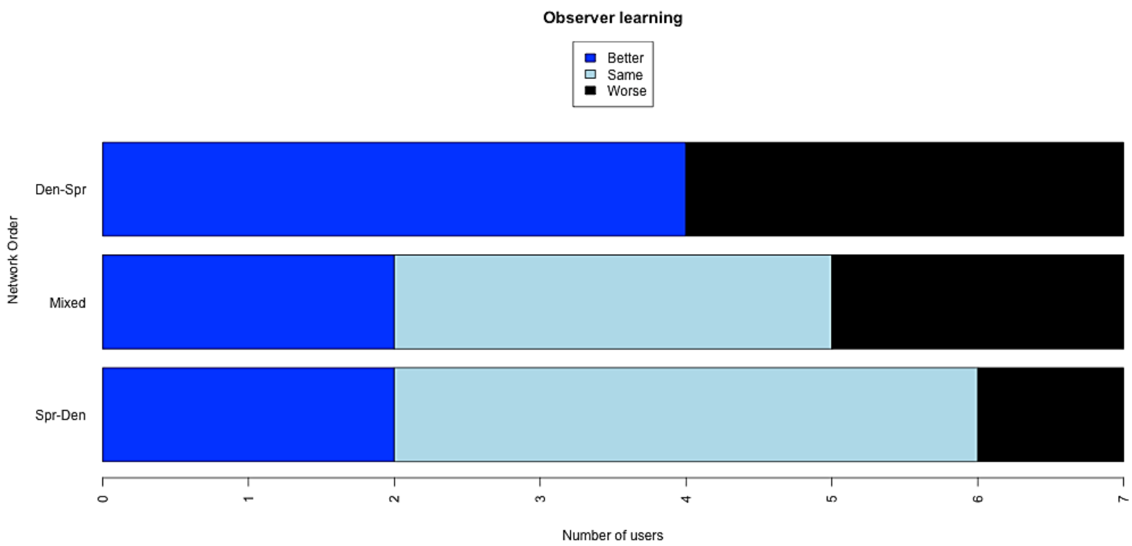


Figure 6.17 Observer performance according to assigned image group. Den – Spr: decreasing complexity, Spr – Den: increasing complexity. Dark blue: observers who performed better at the end of the study; Light blue: observers who performed the ‘same’ at the end compared to the start of the study; Black: observers who performed worse at the end of the study.

Figure 6.17 shows observers performing better at the end of the study in all three image sequence groups, however this was most common in the group with the images starting with dense networks, and finishing with sparse networks (4 observers). This improvement could be attributed to the simpler networks at the end of the set however, when improvement is seen in the group with increasing complexity (2 observers); this suggests that learning may have taken place.

It can also be seen that in all three groups, a number of observers performed worse at the end of the sequence; most of these were using the decreasing complexity group (3 observers).

The overall results suggest there was a possibility of learning as overall, there were more observers who performed better at the end, compared to those who performed worse (8 observers). However, given the limited sample size, this cannot be deduced conclusively from the data obtained during this study.

Relationship between prior knowledge/experience and performance

Information relating to the observers' experience was collected as it was hypothesised that this may impact on the ability of the observer to reproduce an identical network.

It was hypothesised that those with anatomical knowledge, experience in the analysis of anatomical features from images, experience of operating Adobe® Photoshop® and/or experience of operating R© would perform better than those without. The number of observers within each category are shown in (Table 6-7).

Table 6-7 The number of observers within each category (none, minimal, moderate or extensive) relating to each area of knowledge/experience

	Anatomical knowledge	**experience of hand feature analysis**	**operation of R© software**	**Operation of Adobe® Photoshop®.**
none	2	15	16	1
minimal	4	0	4	5
moderate	6	1	1	10
extensive	9	3	0	5

An ANOVA was performed on this data to establish whether this hypothesis was upheld. It should be noted that these tests were applied to give an indication of the effect, however due to low numbers of observers within each experience category (Table 6-7), coupled with the complexity of the data analysed, the dataset failed to meet ANOVA criteria; therefore the results should not be interpreted without consideration of this issue. Despite this, the results indicated that there was no statistically significant difference between the performances of the groups of observers when considering their level of anatomical knowledge and experience of R© software (Table 6-8, Figure 6.18).

Table 6-8 ANOVA output from the analyses of the effect of observer experience.

Category	**P value**
Anatomical knowledge	0.766
Experience of hand feature analysis	0.846
Experience of R Studio©	0.357
Experience of Photoshop	0.363

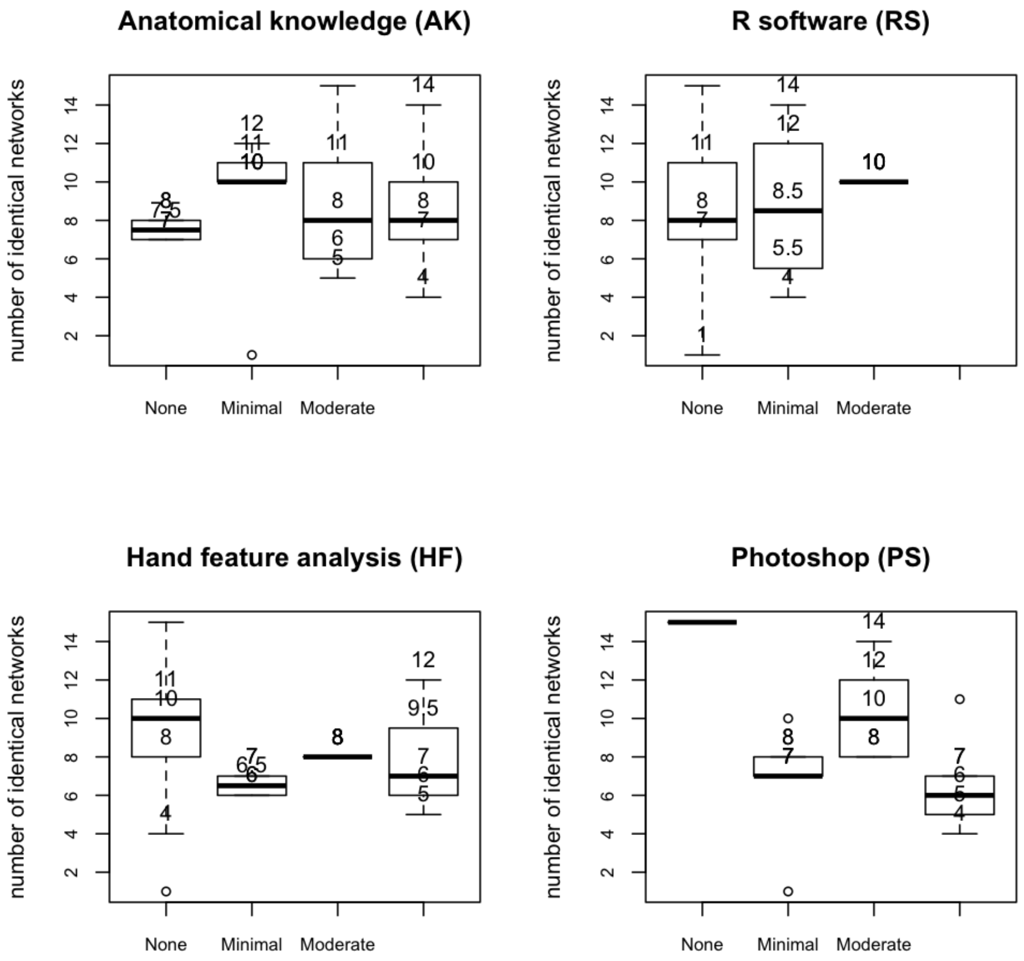


Figure 6.18 The effect of experience on the ability to identify an identical network.

6.5 Observer reliability study discussion of results

Ascertaining the validity of an innovative forensic technique is vital to its acceptance in legal proceedings (Dror *et al.*, 2006; National Research Council of the National Academies, 2009; Page *et al.*, 2012).

The current research carried out observer studies to establish the validity of extracting vein network information from digital images in a manner that enables subsequent quantitative analysis of the vein network.

It can be appreciated that the human observer is inherently subjective and that some errors in pattern interpretation may exist. However, due to current lack of automated software available that can extract the vein pattern from a visible light photographic image for forensic purposes, it was necessary to test the manual extraction method.

Intra-observer

The intra-observer study set out to establish whether the method used to extract vein networks was applied repeatedly by one observer (the author) on more than one occasion.

Visual examination of performance

In a 2 stage process it was important to assess both stages independently, as well as the end result. The first stage of the methods involved manually tracing the vein pattern onto the digital image. It was therefore possible to visualise all traces simultaneously by merging all traces in Photoshop. From this it was seen that the majority of traces did not match precisely; an unexpected result as the trace in the observer study was produced using a template. This lack of consistency highlights the subjective effect of a human user. Despite this, it could be argued that precision in the placement of ‘lines’ during the tracing stage was of less importance than when a ‘tracing only’ method is used (Meadows, 2011), due to the fact that the subsequent analysis of the vein network was only reliant on features of the network i.e. joining points, start and end point etc. Because the observer was aware of the requirements of the analysis it is possible that less attention was paid to precise line placement. For the purposes of this study, it was of greater importance to assess the next stage of the extraction process, which would result in the production of a ‘network’ from the visual pattern. It was therefore important to also assess the vein pattern after it had been translated to a network.

Assessment of the vein pattern as a network: pairwise comparisons

Due to the lack of statistical normality in the vein network data, pairwise comparisons were the most appropriate and stable approach to assess the differences between the way the network was recorded in each repeat. From this, it could be seen that just over half (52%) of the networks were recorded as isomorphic in all 6 repeats. It should be borne in mind that this value relates to networks being isomorphic, and therefore does not account for networks which were very similar, e.g. 1 edge difference. Extended analyses of this data could be explored in more depth.

The pairwise comparisons also highlighted that the worst overall performance was observed in the dense networks suggesting network complexity influences the ability to repeatedly identify vein network features.

Comparison of visual and statistical approaches

It is important to compare the two stages of the process, to identify potential sources of error; which will enable development of the method to minimise this error as far as possible.

When comparing the results of the visual and statistical assessment of the vein network, in some cases, it was found that where a network was shown to be traced precisely, the statistical interpretation showed that not all repeats were recorded the same. However, the converse was also found in other cases. Upon examination of the traces, the majority of the traces did not match exactly; however, this was not found when comparing this to the statistically analysed data.

This indicates that visual examination of traces does not always equate to the topological information that has been recorded for the purposes of quantification.

This discrepancy between the visual examinations and the statistical output may be indicative of the source of error when assessing vein patterns using the methods described in this study. The traces may appear the same, but error occurred when information was transferred from the traced images to the R© template. Although this source of error has been highlighted in this study, this should not detract from the benefit of assessing vein patterns via network analysis.

It is appreciated that precise tracing is of utmost importance when it is only the trace which is being assessed (as current forensic methods (Meadows, 2011)); however when tracing is one of two stages involved in information extraction, to which the subsequent stage is key to data recording, the precision of tracing becomes less important. Essentially, the re-tracing of a manual trace is a redundant task; however, it aids the user in clarification of data points (nodes), and was therefore deemed necessary in this study. In relation to this, tracing regarding key feature points (bifurcations etc.) is of significant value to subsequent network analysis and should therefore be performed with great care.

The comparison of both stages of the data extraction process highlights the importance of a human observer to check the output in relation to the original data source.

Observer performance regarding motif detection

Further to the number of edges detected, pairwise comparisons were conducted with regard to motif detection, giving a more detailed assessment of observer performance. 3 and 4 node motif detection showed similar performance, suggesting that motif complexity does not influence observer detection of these structures.

Observer performance regarding prominent vein network features

Certain features of vein networks are important to discuss, as due to their relative rarity, they have potential of being an individuating feature. Meadows (2011) found 23% of the sample to have loops (from visible light images), however Aiken (2014) found significantly more from IR images (70%). In terms of how well these structures are identified by observers, Meadows (2011) showed that in VL images (after lines and branches) loops and then intersections were the most reliably identified features.

The current study shows that intersections were consistently identified in all 6 repeats, with the exception of 1 network (URN 8, sparse). They were mostly identified in the dense networks, followed by the sparse, with the intermediate networks having the least intersections present.

The identification of loops across the repeats in the intra-observer study occurred in all but two networks (URN 8, sparse and URN 4, intermediate, (Figure 6.15). They were mostly observed in the dense networks, followed by the intermediate, with the sparse showing the least loops. This result does not agree with the findings from Meadows (2011), where loops were more reliably identified than intersections.

Overall, the results from this study show that when present, intersections or loops are consistently identified. This may be attributed to the relatively low prevalence in the sample, or perhaps that these features are more distinct than edges and nodes and therefore appear more obvious to the observer.

This consistency in identification of the feature should be regarded as an indication that these features can be identified with confidence in a forensic scenario.

Overall the performance of the observer was shown to be repeatable, irrespective of network complexity. The differences observed could be due to expected error and fluctuations in the data. Further studies would benefit from a larger sample of images, and additional repeats so that more in depth statistical analyses can be conducted.

Inter-observer

The inter-observer study set out to establish whether the method of extracting vein patterns from digital images was repeatable by different observers, exhibiting a range of experience levels.

To assess the differences in responses from the observers, each network was compared to a reference network, produced by the author, to determine the level of similarity between the two. Networks were graded as identical, similar or dissimilar in relation to the number of edges identified.

Observer performance and network complexity

It was expected that since more complex networks contain more pattern information; this presents more opportunity for variation in the interpretation of pattern detail. This was shown to be the case (Figure 6.16).

The sparse networks showed the highest number of identical network reproductions (59.52%); followed by the intermediate (39.88%), with the dense networks reporting the lowest number of identical network reproduction (32.54%) (Figure 6.16, Table 6-6). This difference suggests that simple networks are more consistently reproducible, but moderate to more complex networks are more difficult to reproduce repeatedly.

This supports the hypothesis that network complexity influences the ability of an observer to identify the features within a network, however, due to the complexity of the data and relatively small sample size, in depth statistical testing could not be performed, therefore the results may give an indication that complexity influences observer performance, but cannot be reported with confidence. The sample size was deemed an appropriate size to give an indication of a result. Recruitment of a larger pool of participants would have taken considerably more time and resources, which was deemed extraneous to the remit of this study, as a portion of a larger project.

Contrary to the findings in the current research, Meadows (2011) found that as network complexity increased (complexity based on the number of edges in a network), two out of three observers performed better, whilst the remaining observer performed worse.

Given that this study was performed using mostly untrained observers, this shows that when presented with simple to intermediate level networks, little training is required to enable the observer to identify the features, however when presented with networks of higher complexity, observers with little experience or training struggle to repeat the network. It would be beneficial to extend this study to assess whether different levels of training influence observer performance.

Influence of learning on observer performance

Prior to participation in this study, some observers had no training or direct experience of applying the techniques employed in this study; therefore it was reasonable to expect that some degree of learning would take place during the study, i.e. it was expected that observer performance would improve in the latter stages of the study after having gained experience from the early stages.

To minimise the effect of network complexity when assessing learning, the observers were provided with the images in different sequences. Although overall, there was an indication that observer performance improved by the end of the study, regardless of image sequence it cannot be stated if this was statistically significant. The indication however, suggests that minimal experience is required before a user is proficient in terms of network reproduction. Due to the relatively small sample size used in this study and the complexity of the data, an in-depth statistical interrogation was not possible and therefore the study cannot provide conclusive evidence to support that learning has occurred. It would be useful to extend this study to include more images and more observers, so that statistical analyses could be extended. It would also be beneficial to investigate whether other factors contribute to the performance of observers, such as indirect experience of the methods. This may relate to observer experience in image analysis in relation to other fields of work, or skills such as an understanding of networks, and therefore an appreciation of their recording.

Relationship between prior knowledge/experience and performance

It is important to be aware of how experience and knowledge influence observer performance as this may be useful when selecting a forensic practitioner, and to estimate the level of training required for a practitioner to be proficient.

It was hypothesised that the previous knowledge and experience of the observers would influence their ability to identify the features of a vein network successfully.

However, it was found that there was no statistically significant relationship between the performances of the observers and their level of anatomical knowledge, experience of hand feature analysis, operation of R Studio© or experience of Photoshop. The level of anatomical knowledge required to perform this study was minimal as a manual trace of the vein pattern was provided to the observers, from which they had to ‘trace’. Minimal anatomical knowledge may have been beneficial to understand the direction of blood flow in the vein for the assignment of directional information, however this information was stated in the information pack so all observers were aware of all relevant information. It was therefore not surprising that anatomical knowledge was shown to be an insignificant factor in observer performance. It theorised that experience of hand feature analysis may have been beneficial in this study, but was not found to be the case. The operation of R Studio© was minimal in this study, in that it was solely used for data input, into an existing template for which full detailed instructions were provided. Had further operational tasks been involved such as analysing the data, this may have presented a different result; therefore again it was not surprising that this lack of experience did not affect observer performance. Experience of Photoshop may not have influenced the performance of the observer directly, but it was noted anecdotally that those who were less experienced in Photoshop needed more assistance during the study, and took longer to complete the task.

It is important to appreciate that the observers' previous knowledge was self-assessed, and in a subjective manner, using a scale; variations in 'actual' experience levels, as opposed to perceived, may have been present.

Contrary to the findings in this study, another study looking at the repeatability of vein pattern extraction from digital images for the purposes of human identification showed that the most reliable performer had experience in anatomy, forensic application of vein pattern analysis (VPA) and some experience with Photoshop, suggesting that these factors may play an important role in observer performance (Meadows, 2011). The differences in findings may be due to more anatomical knowledge being required for the initial tracing of the vein pattern, whilst in the current study, this was prepared for the observer.

The sample size in this study was small, smaller still were the number of observers within each 'experience' category (Table 6-7), therefore statistical analyses should be interpreted with care.

It is difficult to draw robust conclusions with the limited sample size, but initial results suggest that experience or knowledge does not have a significant effect on the ability to extract vein pattern information successfully. As explained, the sample sizes were deemed appropriate for this short study, but it can be appreciated that to draw more robust conclusions, additional resources should be sought to acquire a larger sample of data.

Observer studies: Overall discussion

In the intra-observer study, network complexity appeared to have little influence on the ability to reproduce the networks. Conversely, the inter-observer study, showed performance was better in the sparse networks compared to the dense networks. This difference in performance may be due to the increased experience and knowledge of the procedure by the author (intra-observer) compared to observers who took part in the inter-observer study. This would suggest that with direct experience, observer performance may improve, although this cannot be formally deduced from the results of this study.

From the intra-observer study it emerged that the main source of error arose from the translation of data from the digital image into the R Studio© template. It should therefore be noted that this is a vital step where the utmost care and attention are required to ensure accurate data recording. It is expected that this may increase with further experience and operation of the technique.

To eradicate human error, future studies should consider the development of an automated approach to data extraction from visible light images, however it is thought that a human observer should always oversee the process as it has been shown that automated systems can interpret other structures as veins, such as tendons or shadows on the dorsum of the hand (Bellini, 2010).

It should also be noted that the inter-observer traces were compared to a reference network produced by the author. It is impossible to ascertain the ‘correct’ vein pattern, so the reference comparison method was deemed suitable for this study, but it is possible that errors existed in the reference network.

Due to limited sample size in both studies, coupled with the complexity of the vein network data, it is difficult to draw substantial conclusions from these studies. However, the indication is that a human observer can extract vein pattern information reliably from a digital image although further studies are required to establish the level of training required.

6.6 Superficial vein pattern quantification: main study

This section addresses three aims;

1) investigate the prevalence and distribution of vein network features

2) investigate how feature distribution is affected by biological characteristics

3) investigate the influence of case specific conditions.

6.6.1 Material and methods

All images used in this study were extracted from the VPP database. Right and left hands of 53 individuals were photographed in both the clenched fist and the semi-pronated position, and each hand pose at three levels of image quality (n = 636) (section 5.3, Table 5-5). A selection of images from this database were used to address the different aims; which will be specified in the relevant sections. Vein network data was extracted from the images, following the methods outlined in section 6.1.2 (R files in appendix J).

Analysis

Analysis commenced with the production of descriptive statistics in R©. The median value was used in most cases to describe the average, due to the fact that the data was not normally distributed; therefore the mean value would provide a poor representation of the spread of the data by being too heavily influenced by, or too sensitive to, the extremes of the data set. Further to this, subsequent parametric tests were interpreted with care.

The statistical comparison of networks of different sizes was not a trivial task. The multidimensionality that results from inter-connected node and edges increase the number of possible network configurations. An increase in the number of nodes calls for extensive mathematical and statistical analyses before defining a null model to assess the statistical difference between two networks. Such analyses require the derivation of moderately large targeted datasets and the development of appropriate statistical tools, both of which are beyond the scope of this thesis. Therefore, while an exploratory statistical analysis of network differences will be presented, hypothesis testing was not included and p values were not derived in all instances. Where possible, traditional statistical methods were utilised, however due to the reasons just outlined, these must be interpreted with care.

The following methods were used where appropriate and according to the variable being tested.

ANOVA testing was employed using the ‘aov’ function in R©, when assessing the continuous variables against categorical variables. An ‘aov’ test fits analyses of variance, assuming normal errors and constant variance (Crawley, 2013).

Correlations were performed when assessing two sets of continuous variables, using the ‘cor’ function in R©, to determine whether there was an indication of interdependency of two variables. A correlation coefficient near 1 indicates that, on average, when one variable increases the other increases proportionally, while a correlation coefficient near -1 indicates that on average when one variable increases the other decreases proportionally. A correlation near 0 indicates that the two variables are independent. To establish the correlation coefficient ($\boldsymbol{r}$) the following equation was used:

Equation 6-2: $\boldsymbol{r} = \frac{\boldsymbol{cov\ (x,y)}}{\sqrt{\boldsymbol{s_x^2 s_y^2}}}$

The two variances of the variables are denoted by s_x^2 and s_y^2. If x and y (the two variables in question) are linearly independent (are not correlated) the value of covariance is 0 (Crawley, 2013).

6.6.2 Results

The results pertaining to the 3 aims of this section are presented in the following sections.

AIM 1: Establish the variation of vein network features.

In this section, data from 9 mp, clenched fist images only will be presented to illustrate the distribution of features without the influence of other variables, including hand pose and image quality, as these may introduce an unknown level of error by affecting the level of detail within the image.

Edge and node distribution

The complexity of a network is multifaceted, and no definition exists in relation to quantification of network complexity. A simple approach is to approximate the complexity of a network by its size, i.e. the number of nodes or edges. On comparatively similar networks, such as those derived from the visible vein pattern of the hand, this was considered appropriate.

The table below shows networks from the 9 mp, clenched fist sub-set of data, and shows them categorised as sparse, intermediate and dense according to the number of nodes and edges (Table 6-9).

Table 6-9 The distribution of edges and nodes across the sample database (9 mp, C image data).

	Edges		**Nodes**	
Category	**Range**	**Number of networks**	**Range**	**Number of networks**
Sparse	0 to 8	23	0 to 9	20
Intermediate	8 to 16	55	9 to 15	57

Dense	16 to 28	28	15 to 24	29

Most of the networks were categorised as intermediate, followed by dense, with the least networks categorised as sparse.

The values from edge and node data suggest a strong relationship between nodes and edges. Upon closer examination, this hypothesis was confirmed, nodes and edges were strongly correlated ($R = 0.995$, $p = <0.001$) (Table 6-10, Figure 6.19).

Table 6-10 Results from the correlation test between the number of nodes and edges.

Correlation factors	**R**	**P value**
Nodes: Edges	0.955	<0.001

A few key points are interesting to discuss; the outlying points marked A, B and C in Figure 6.19. Interestingly, two of the outliers (B and C) have a high number of loops; this would explain the reason for a high number of edges, without the corresponding high number of nodes. To create a loop, many edges are required, but nodes may be ‘recycled’.

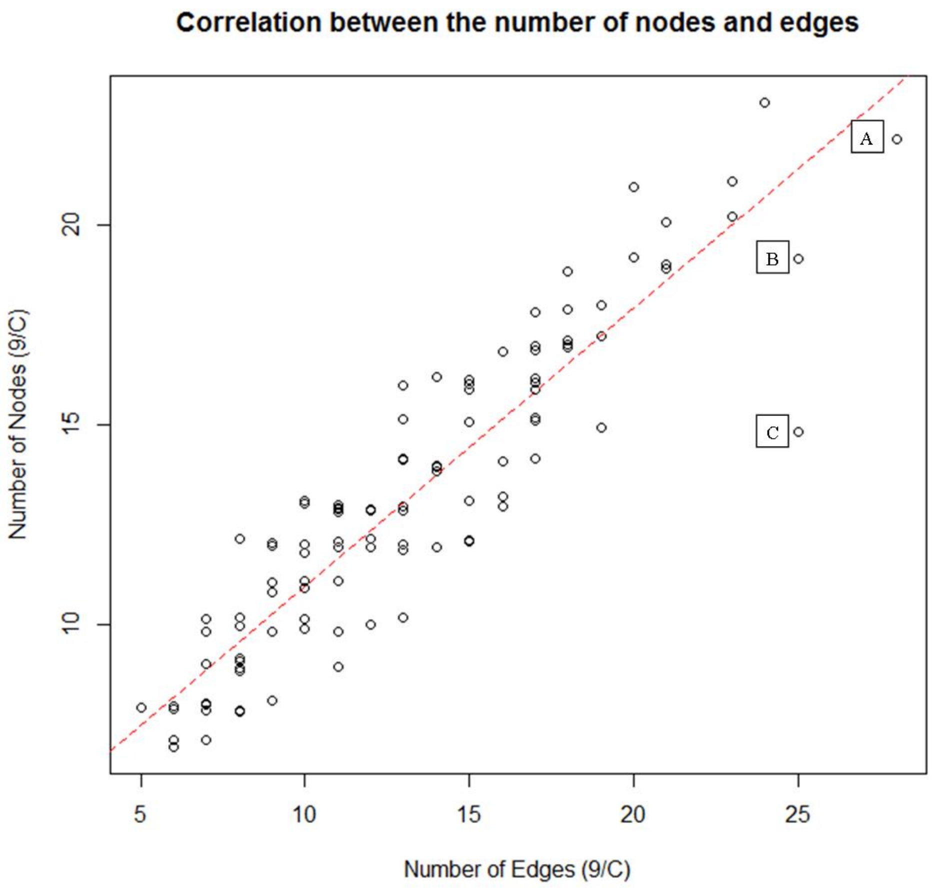


Figure 6.19 Correlation between the number of edges and number of nodes in the networks (9 mp, C image data).

Table 6-11 Network details relating to the outliers in Figure 6.19; A, B and C.

Graph code	**Network ID**	**Edges**	**Nodes**	**Intersections**	**Loops**
A	151_9_C_R	28	22	1	2
B	72_9_C_R	25	19	1	11
C	106_9_C_R	25	15	3	21

Edges

From the histogram (Figure 6.20), it can be seen that data relating to edge distribution was not normally distributed. The median number of edges in a network was 12.5, with half of the individuals possessing between 9 and 17 edges. The individuals in the top quartile possessed more than 18 edges (Figure 6.20).

These individuals possessing edges at the higher end of the scale present a denser and therefore more complex network.

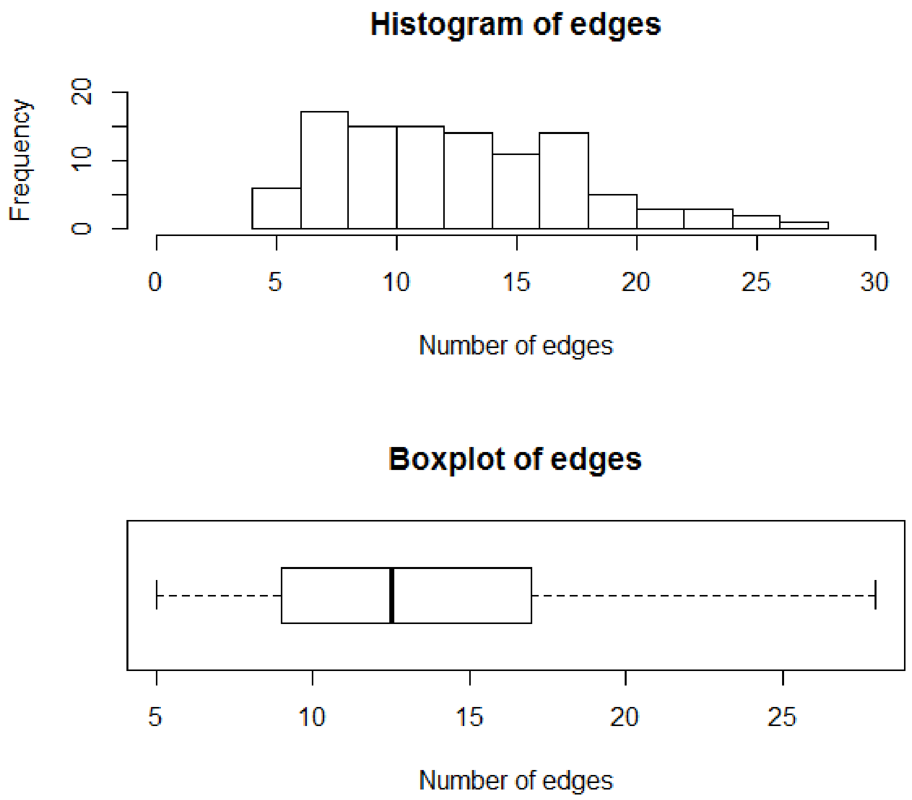


Figure 6.20 Total number of edges (9 mp, C image data).

To visualise the extent of the differences between a 'low edge' and a 'high edge' network, Figure 6.21 is provided; a) URN 106 contains 5 edges, and b) URN 163 contains 24.

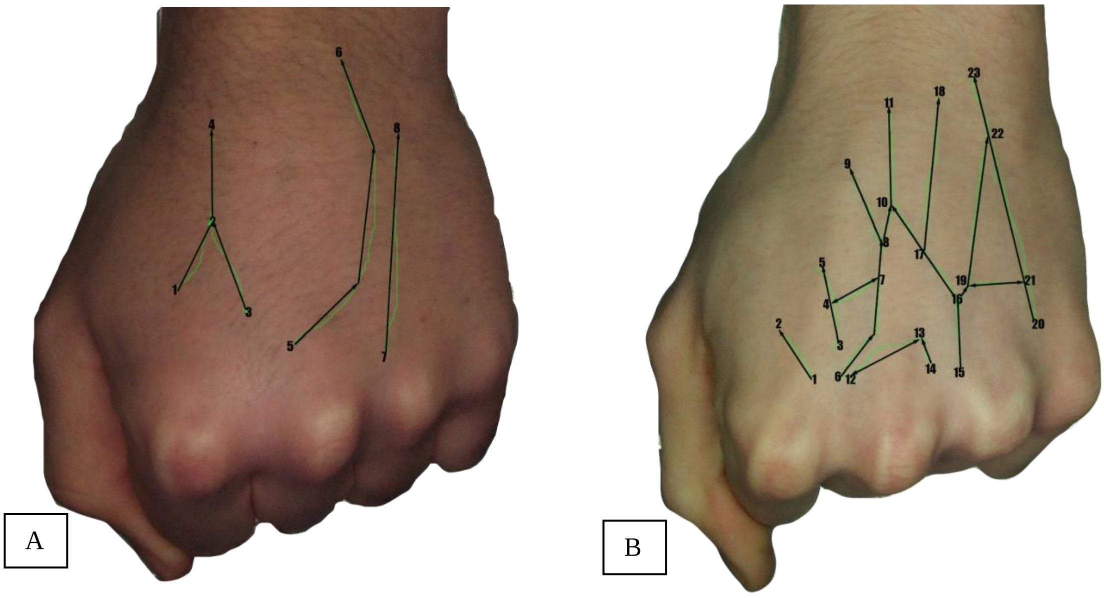


Figure 6.21 Example of a; a) low edge network (URN 106 L), b) high edge network (URN 163 L).

Nodes

The median number of nodes in a network was 13, with 50% of the individuals possessing between 10 and 16 nodes (Figure 6.22).

The minimum number of nodes observed was 6 and the maximum was 24.

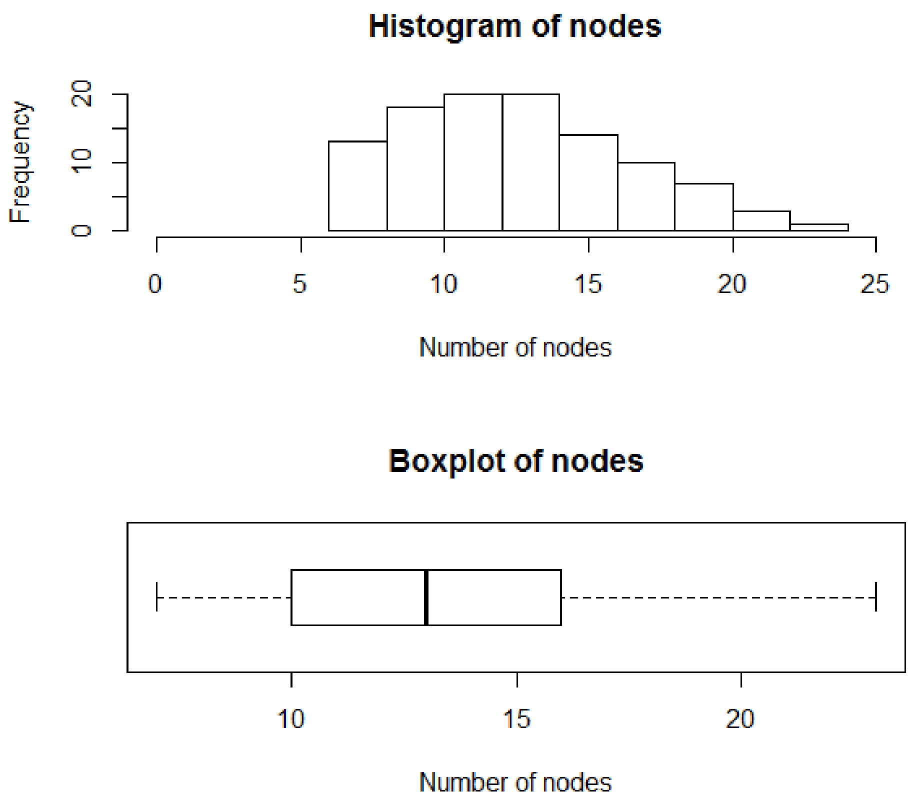


Figure 6.22 Total number of nodes (9 mp, C image data)

To visualise the extent of the differences between a ‘low node and a ‘high node network, Figure 6.23 is provided; URN 171 contains 8 nodes, and URN 86 contains 21 nodes.

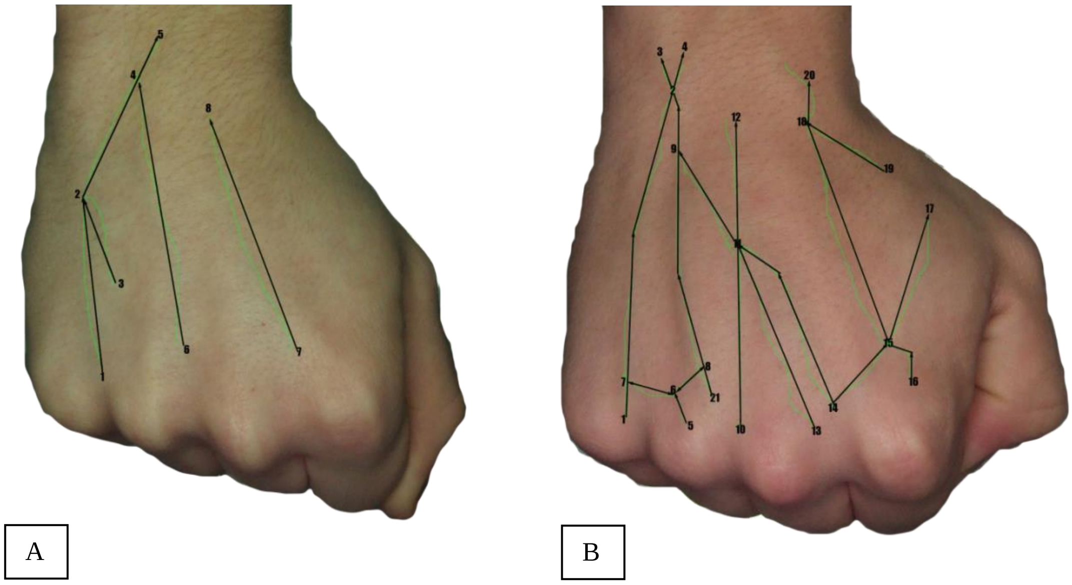


Figure 6.23 Example of a; a) low node network (URN 171 R), b) high node network (URN 86 R).

Motif distribution

Since most networks were relatively small, it was hypothesised that ‘simple’ motifs would be more prevalent than more complex motifs. An example of a simple motif is a 3-node, 2-edge arrangement. More complex motifs would possess more nodes and edges, but importantly, more edges per node; in some cases this would create a loop or an intersection.

There were 7 motifs discovered within the dataset (2, 3 node motifs (A and B) and 5, 4 node motifs (C - G). Figure 6.24 shows the distribution of these motifs on the 9 mp, clenched dataset. The non-loop, 3 node motif (A) was found in 100% of networks, whereas the 3 node loop (B) was more rarely encountered. The two simplest 4 node motifs were identified frequently (C and D), whereas with increasing motif complexity (E – G) it appears that, motif prevalence decreases.

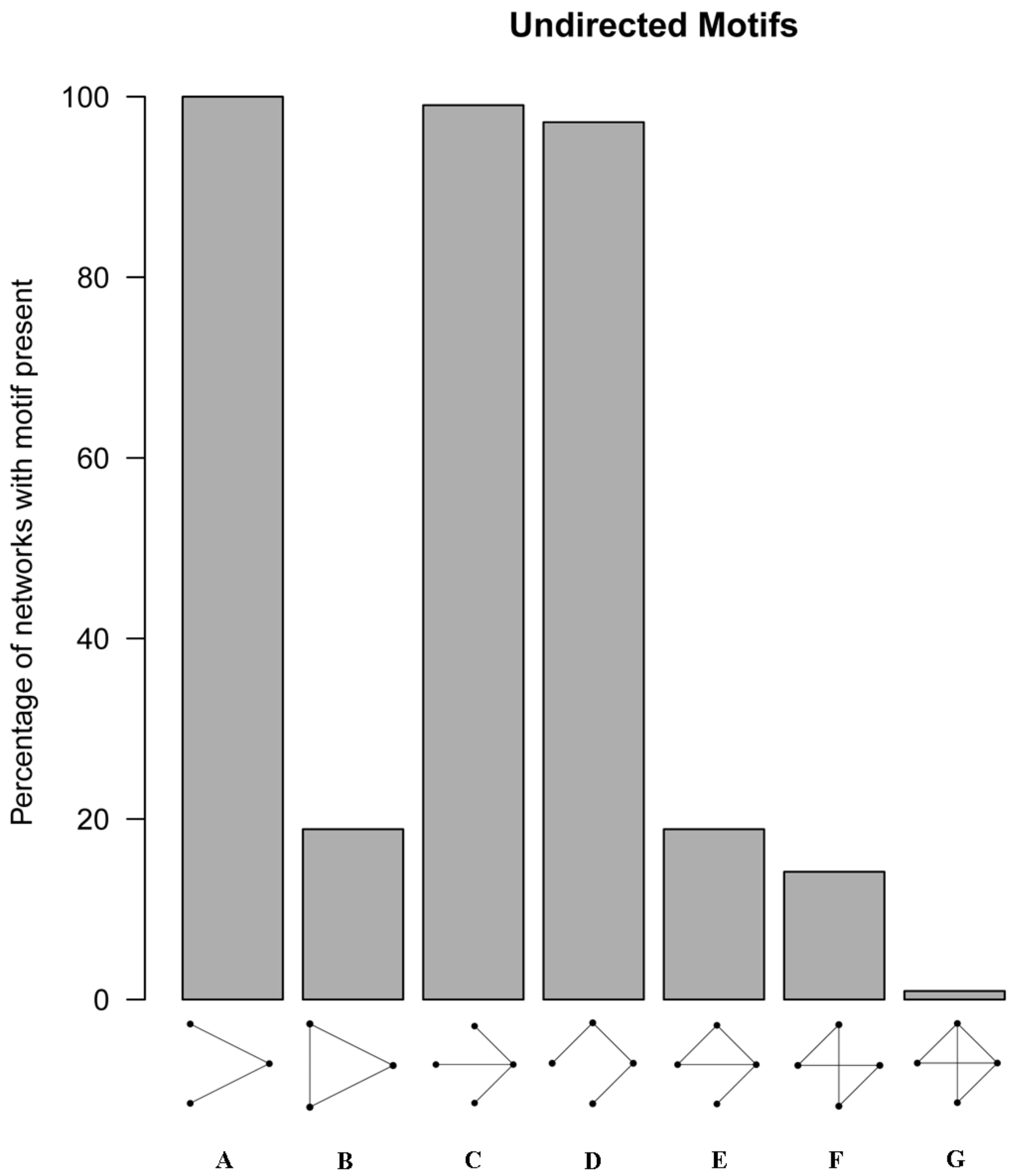


Figure 6.24 Chart showing the distribution of motifs (9 mp, C image data)

Intersections

An intersection is an area where two visible regions of vein cross one another, creating a ‘cross’ structure (Figure 6.25).

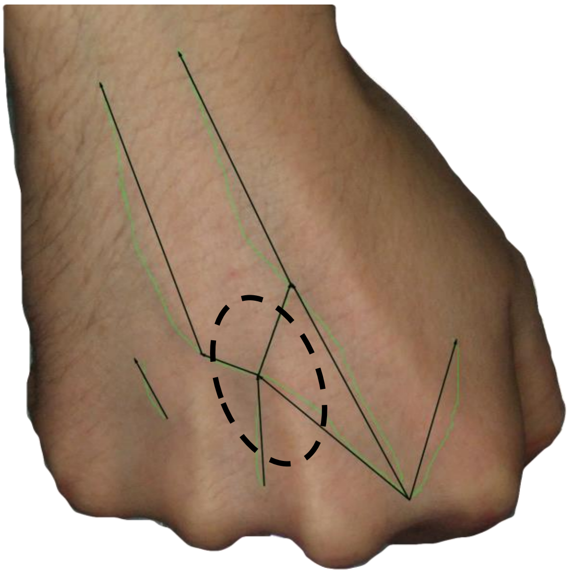


Figure 6.25 Network containing an example of an intersection

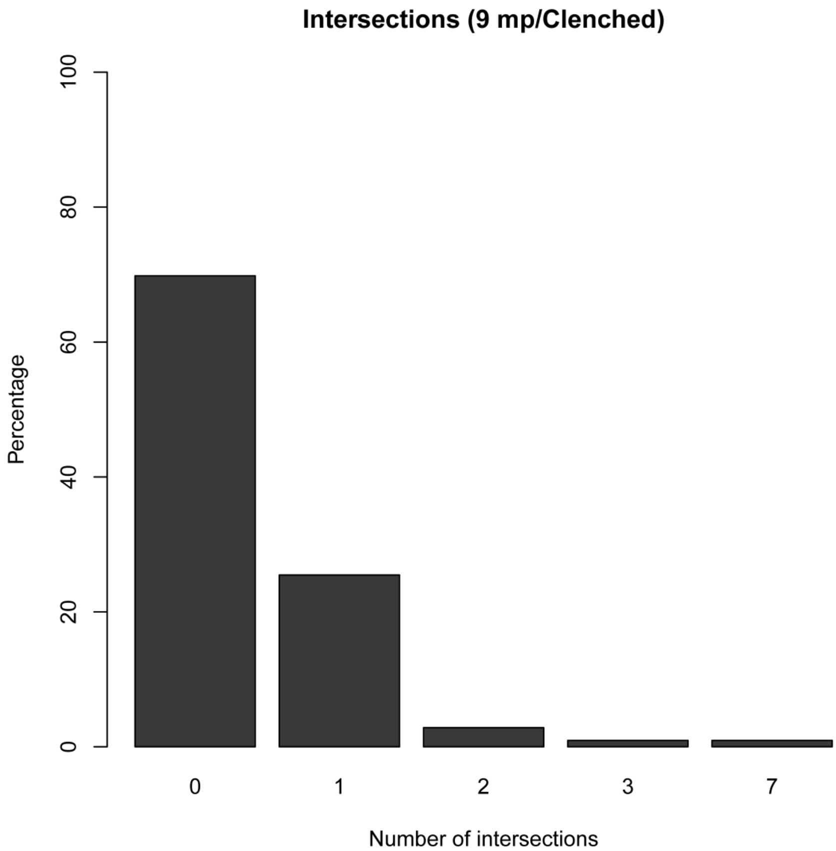


Figure 6.26 Total number of intersections identified within the images on the database.

Figure 6.26 shows that intersections were not present in the majority of networks (69.8%) and were less common than loops. 25.5% of the sample contained one intersection and 2.8% contained two intersections.

Loops

A loop is a type of motif, comprised of three, four or five nodes and represents an area that is entirely enclosed by a region of connected veins (Figure 6.27).

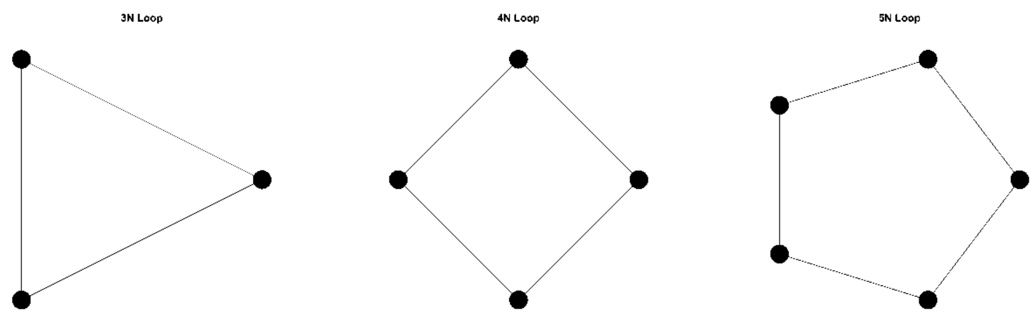


Figure 6.27 Example of a 3 node, 4 node and 5 node loop.

The majority of the networks considered were free from loops of any size, while one loop was found to be present in 29.25% of the sample (considering loops of all sizes). Networks with more than one loop were uncommon, but outliers were observed (e.g. 21 loops in <1% of networks). Simple 3 node loops were the most common; one 3 node loop was identified in 16% of the networks. More complex loops (i.e. 5 node loops) were more rarely encountered, with one 5 node loop found in only 11.3% of the networks (Figure 6.28, Table 6-12).

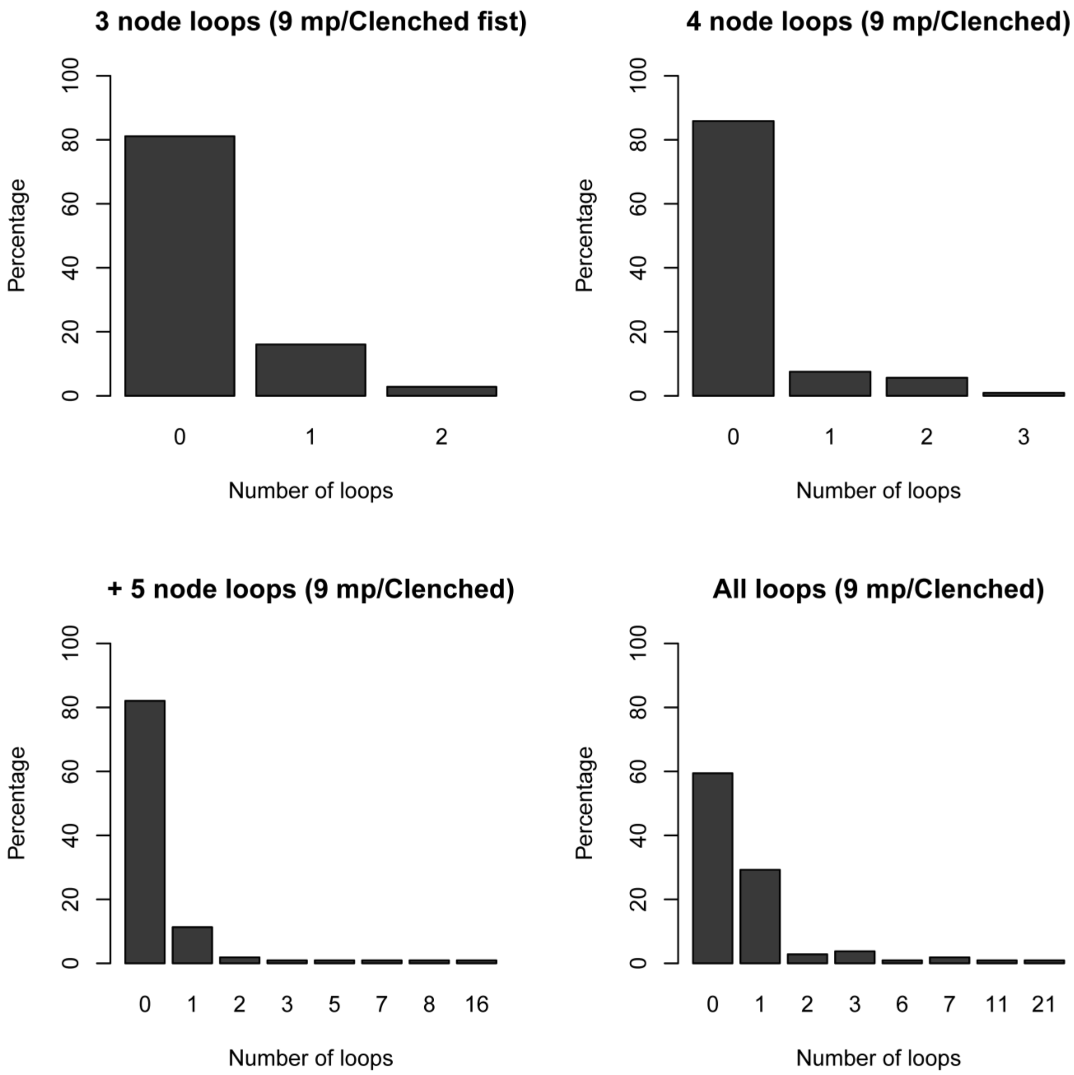


Figure 6.28 Total number of loops; 3 node loops; 4 node loops; 5 or more node loops.

Table 6-12 Percentage of loops (9 mp, C image data).

Loop size	**Number of loops**	**% of loops in dataset**
All loops	0	59.4
	1	29.3
	2	2.8
	3	3.8
	6	<1
	7	1.9
	11	<1
	21	<1
3 node	0	81
	1	16
	2	2.8
4 node	0	85.6
	1	7.5
	2	5.6
	3	<1
5 + node	0	82
	1	11.3
	2	1.9
	3	<1
	5	<1
	7	<1
	8	<1
	16	<1

Determining complexity of a vein network

To explore the complexity of the network beyond feature counts, combinations of selected features were considered.

It was shown earlier that as the number of edges increases, the number of nodes increases proportionally (Figure 6.19).

Given this finding, it was likely that as the number of edges and nodes increased the number of loops would also increase. It was found that networks with loops contained a significantly greater number of edges than networks free from loops (p = <0.001).

However, it was found that the number of edges (r = 0.5) or nodes (r = 0.268) and the number of loops did not display a strong correlation (Table 6-14, Figure 6.29).

Where loops were present, it was more likely that the number of nodes were higher (p = <0.001). Despite this, the number of nodes and the number of loops were not strongly linearly correlated (r = 0.268) (Table 6-14, Figure 6.30).

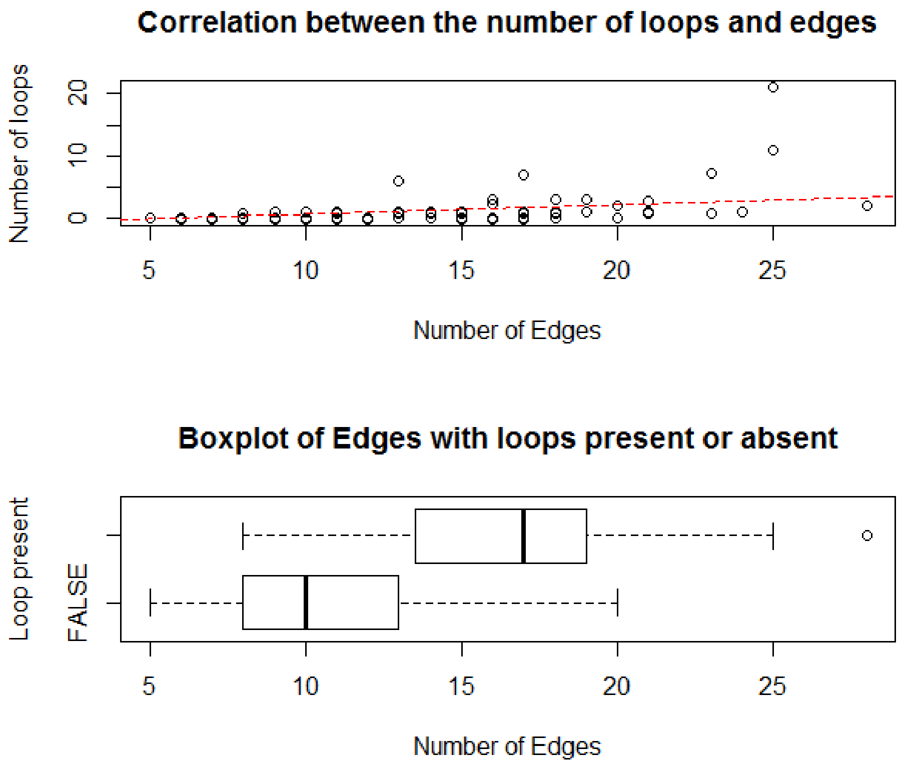
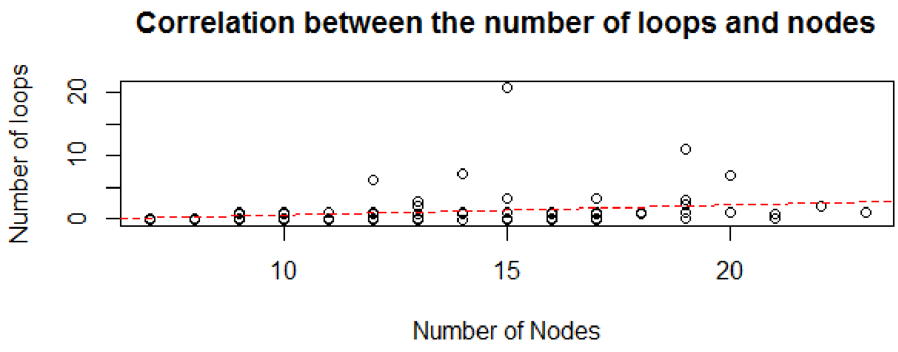


Figure 6.29 Relationship between loops and edges (9 mp, C image data).



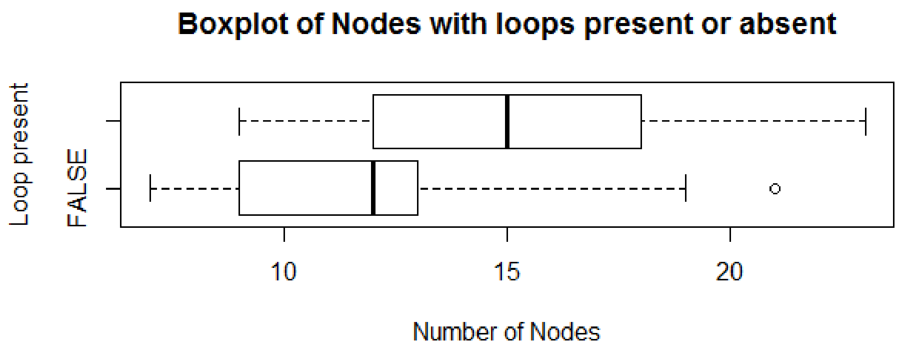


Figure 6.30 Graphs showing the relationship between loops and nodes (9 mp, C image data)

Table 6-13 ANOVA output for the presence of loops and the number of edges/nodes.

	Degrees of freedom	**Sum of squares**	**Mean square**	**F statistic**	**P value**
Edges: Loops	1	9.453	9.453	61.05	<0.001
Residuals	104	16.104	0.155		
Nodes: Loops	1	5.794	5.794	30.49	<0.001
Residuals	104	19.763	0.190		

Table 6-14 Results from the correlation test between the number of edges/nodes and the number of loops.

Correlation factors	**R**	**P value**
Number of edges: number of loops	0.500	<0.001
Number of nodes: number of loops	0.268	0.006

The same hypothesis was considered for the presence of intersections: with increasing number of nodes and edges, it was hypothesised that the presence of intersections would also increase.

Figure 6.31 and Figure 6.32 show that the same trend as loops was observed; when an intersection was present, it was more likely that the number of nodes and edges were higher, although this was not statistically significant in the case of nodes (intersections and edges: p = <0.001; intersections and nodes: p = 0.092) (Table 6-16, Figure 27 and 28 bottom).

However, again it was true that the number of edges and nodes were not strongly linearly correlated with the number of intersections (intersections and edges: r = 0.307; intersections and nodes: r = 0.232) (Table 6-15, Figure 6.31 and Figure 6.32).

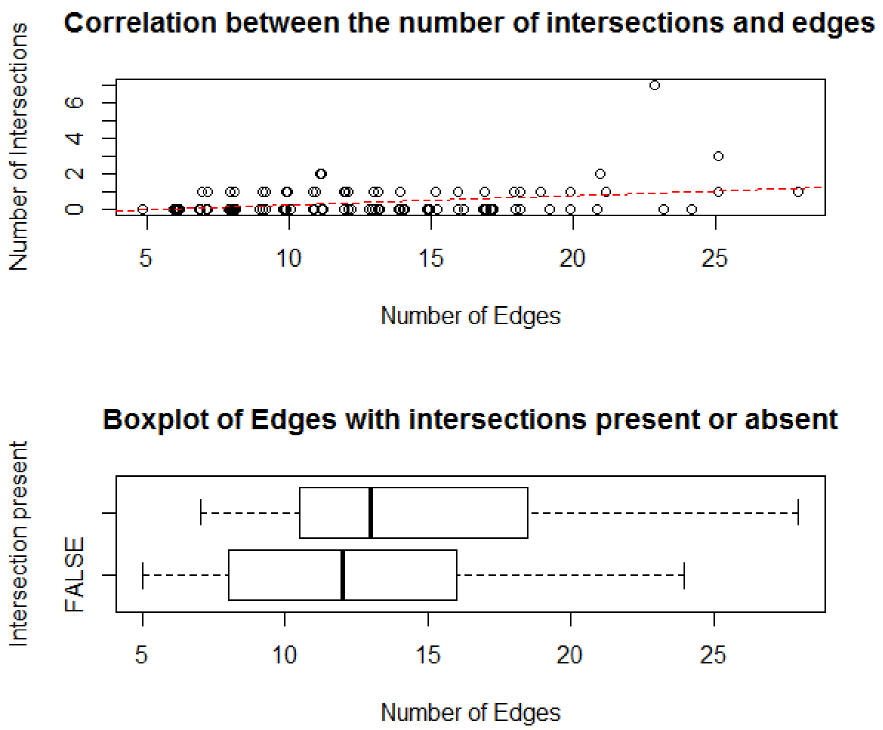


Figure 6.31 Relationship between intersections and edges (9 mp, C image data)

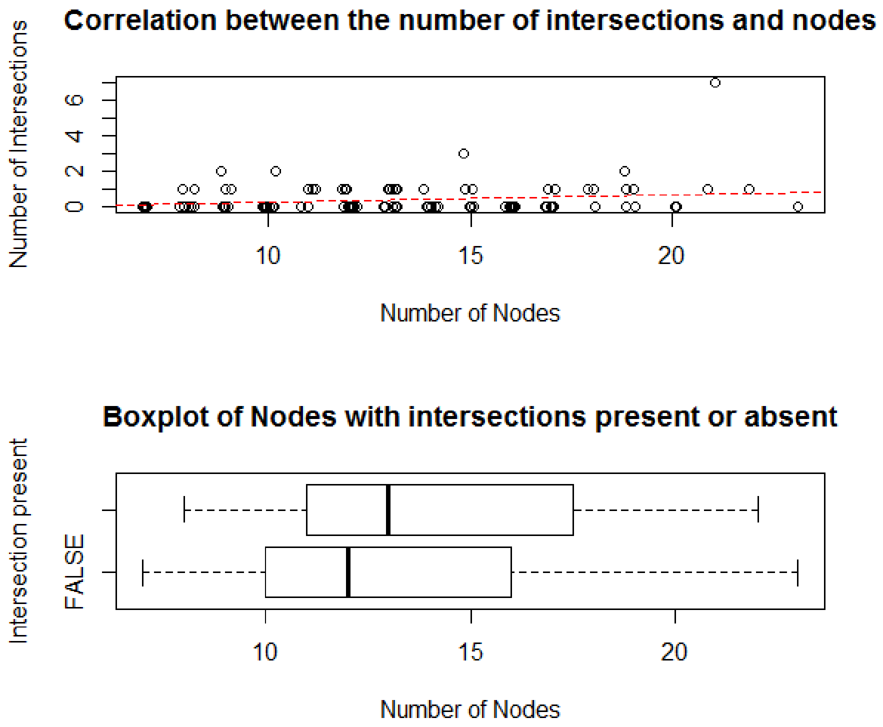


Figure 6.32 Graphs showing the relationship between intersections and nodes (9 mp, C image data)

Table 6-15 Results from the correlation test between the number of edges and intersections.

Correlation factors	**R**	**P value**
Number of edges: number of intersections	0.307	0.001
Number of nodes: number of intersections	0.232	0.017

Table 6-16 ANOVA output for the presence of intersections and the number of edges/nodes.

	Degrees of freedom	**Sum of squares**	**Mean square**	**F statistic**	**P value**
Edges: Intersections	1	1.064	1.064	5.2	<0.001
Residuals	104	21.276	0.205		
Nodes: Intersections	1	0.603	0.603	2.884	0.092
Residuals	104	21.737	0.209		

AIM 2: Influence of biological characteristics on the presence of vein network features

Each biological characteristic (age, weight, body fat percentage and side) was tested to establish whether they had an effect on the presence of vein networks features. This analysis was carried out on the images of highest quality parameters (9 mp, clenched fist) to minimise error from non-standardised images.

Effect of age

The age range of the sample population was 18 to 39 years, with both the mean (22.8 years) and mode (18 years) in the lower end of the range. The age of the individual was shown to have no linear correlation with the number of nodes (r = -0.054) or edges (r = -0.050) (Table 6-17, Figure 6.33).

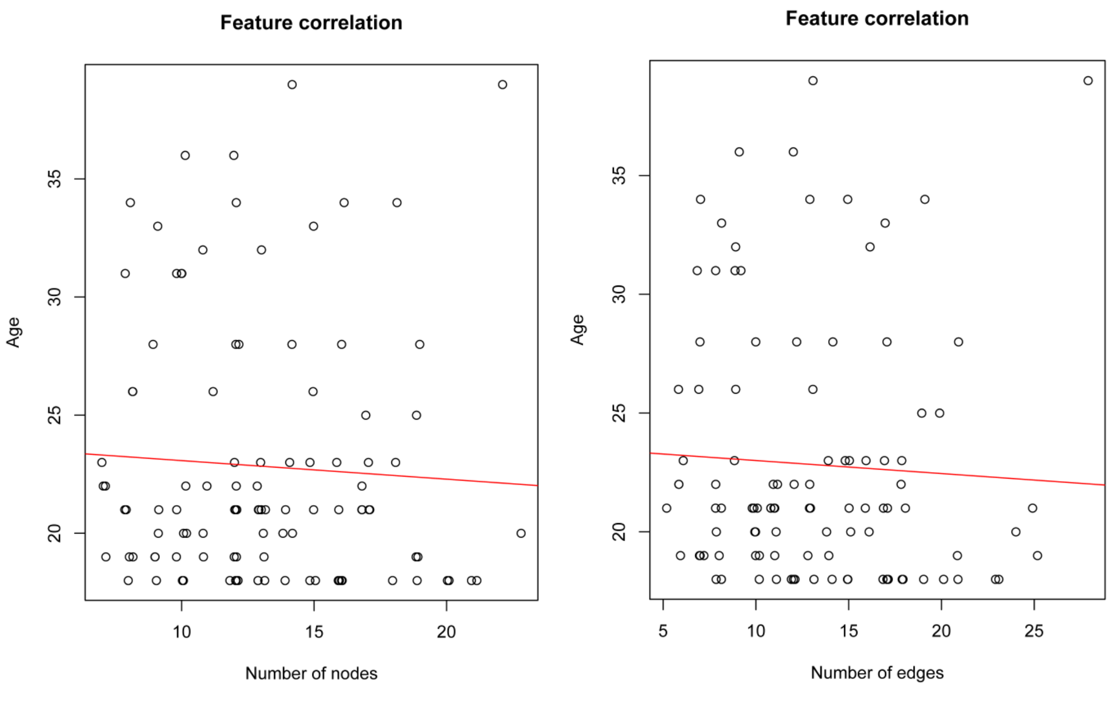


Figure 6.33 Correlation between age and the number of nodes and edges.

Table 6-17 Results from the correlation test between the number of nodes and age.

Correlation factors	R	P value
Age: Nodes	-0.054	0.578
Age: Edges	-0.050	0.608

Effect of weight

The weight range of the sample population was 57.2 to 122.7 kilograms (kg); the mean weight was 80 kg and mode 74.9 kg.

It was hypothesised that with increased weight, less vein pattern would be discernible, however it was shown that the weight of the individual was not linearly correlated with the number of nodes (r = -0.095) or edges (-0.099) (Table 6-18, Figure 6.34)

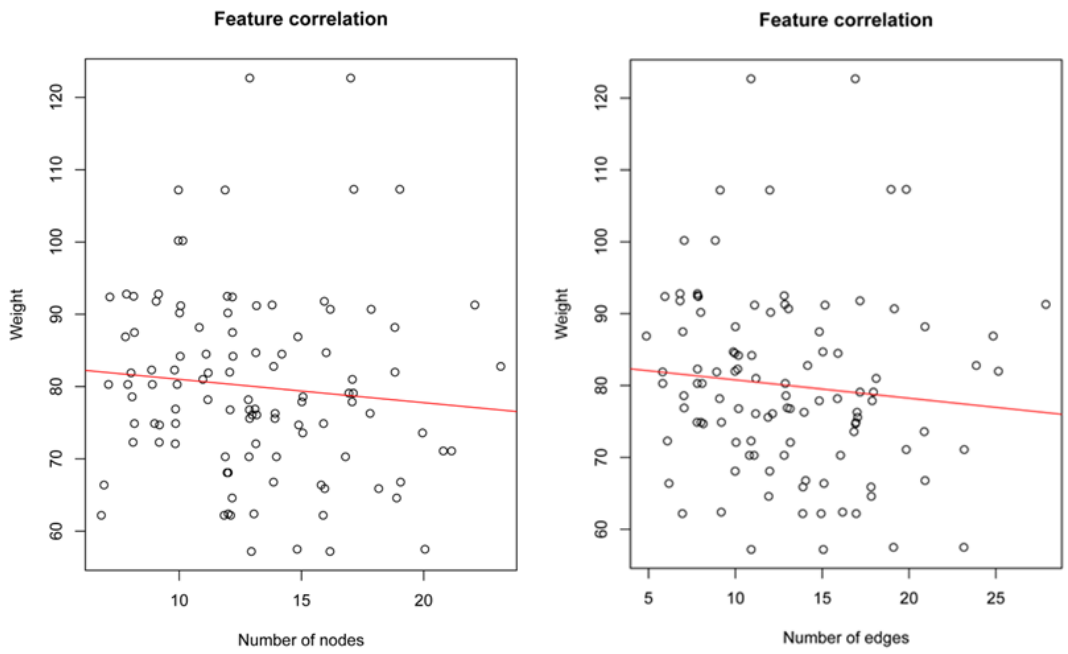


Figure 6.34 Correlation between weight and the number of nodes and edges.

Table 6-18 Results from the correlation test between the number of nodes and weight.

Correlation factors	**R**	**P value**
Weight : Nodes	-0.095	0.33
Weight : Edges	-0.099	0.312

Effect of body fat percentage

The range of total body fat percentage of the sample population was 6.2% to 33.3%, the mean was 17.49% and mode 13.8%.

It was hypothesised that with increased body fat percentage, the features of the vein pattern would be less discernible. It was found that the body fat percentage of the individual was weakly correlated with the number of nodes (r = -0.197) or edges (r = -0.230) (

Table 6-19, Figure 6.35), and that this result was statistically significant. It shows that as body fat percentage increases, the number of nodes and edges decreases.

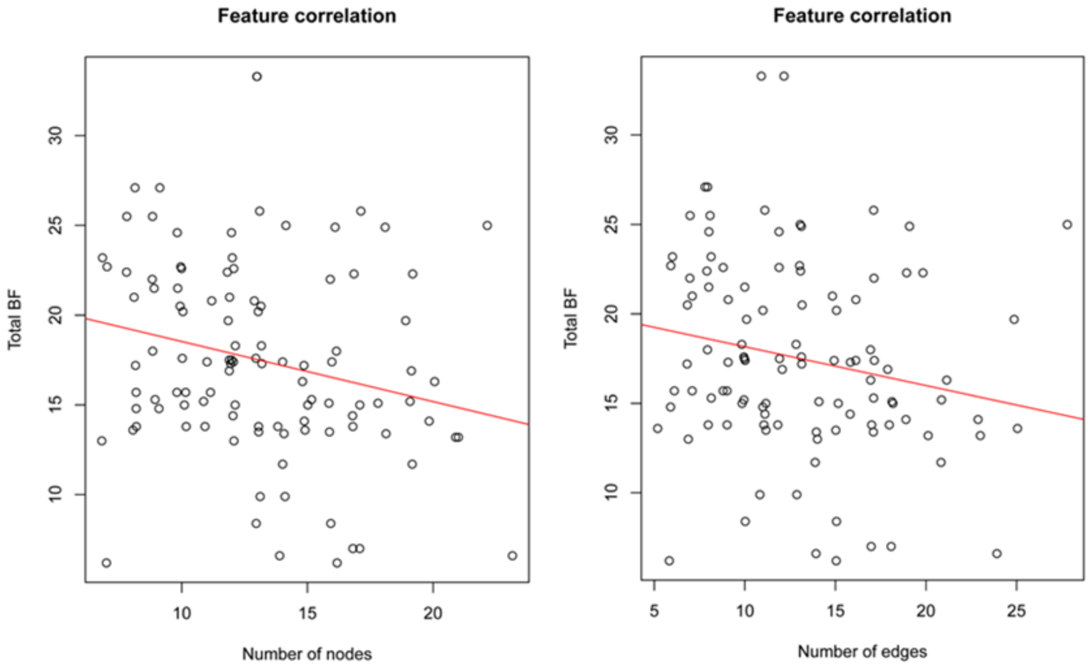


Figure 6.35 Correlation between body fat percentage and the number of nodes and edges.

Table 6-19 Results from the correlation test between the number of nodes and body fat %.

Correlation factors	**R**	**P value**
Body fat % : Nodes	-0.23	0.017
Body fat % : Edges	-0.197	0.042

All correlation results relating to the effect of biological characteristics are summarised in the following matrix (Table 6-20).

Table 6-20 Matrix summarising the p values from the correlation tests between vein network features and biological characteristics. * indicates a statistically significant relationship.

	Nodes	**Edges**
Age	0.578	0.608
Weight	0.33	0.312
Total BF%	0.015*	0.042*

Effect of body side

It was hypothesised that body side would not affect the level of vein network detail. This was seen from the results of ANOVA testing; there was no statistically significant relationship observed for body side and the number of edges (p = 0.519) and nodes (p = 0.36) (Table 6-21, Figure 6.36).

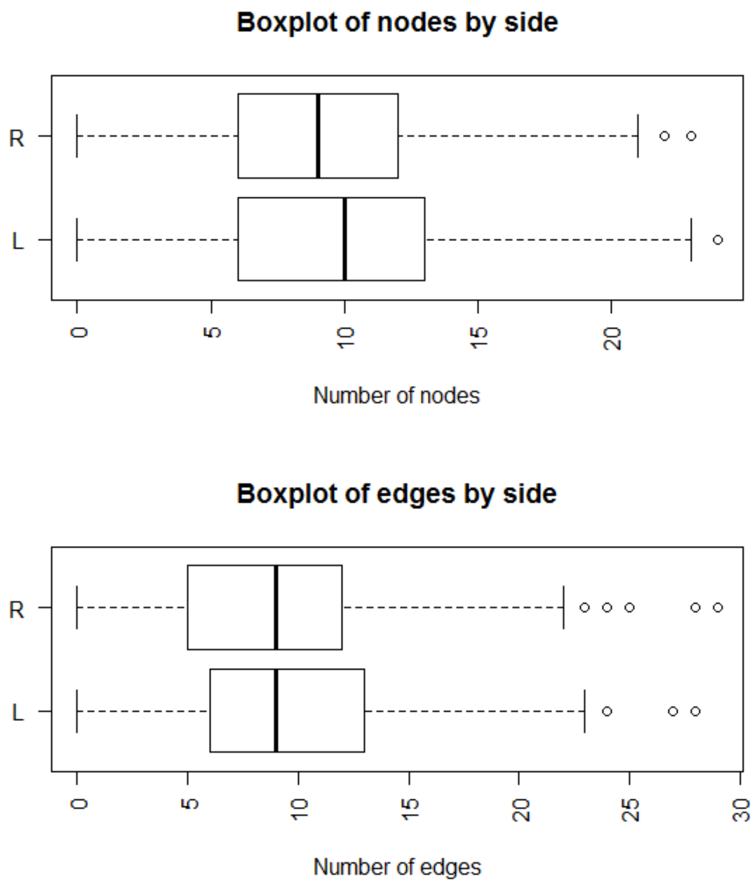


Figure 6.36 Distribution of edge and nodes in left and right hands.

Table 6-21 ANOVA results relating to number of edges and nodes, and body side.

	Degrees of freedom	**Sum of squares**	**Mean square**	**F statistic**	**P value**
Edges : Side	1	13	13.31	0.415	0.519
Residuals	634	20310	32.03		
Nodes : Side	1	20	19.72	0.838	0.36
Residuals	634	14919	23.53		

Body hair and obscured region of interest

It was hypothesised that when hair was present, this would affect the visibility of the vein network and reduce the number of features observed. When considering the number of nodes and edges observed, it was found that hair presence or absence was insignificant (Figure 6.37, Table 6-22).

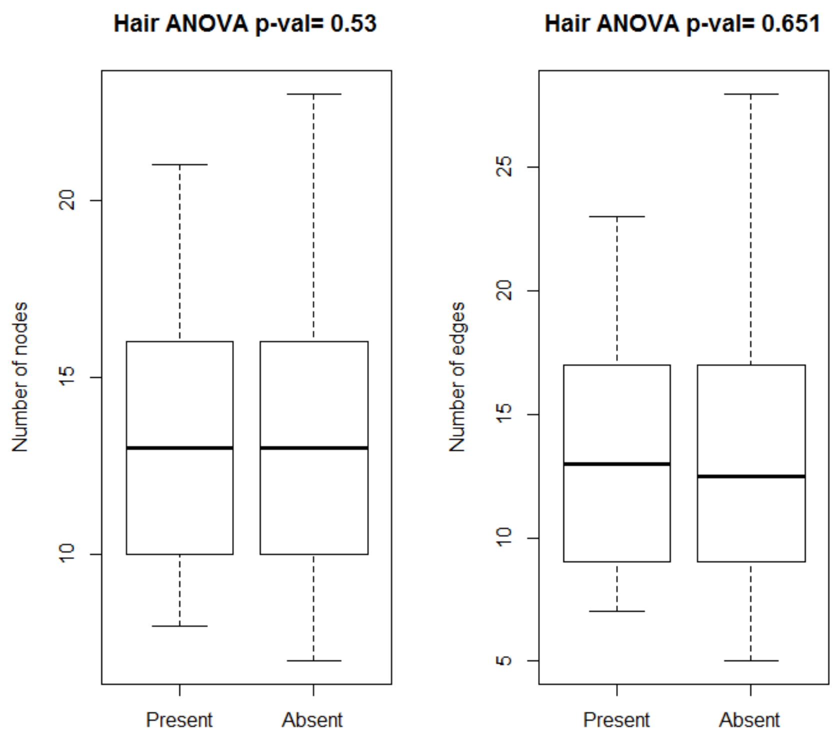


Figure 6.37 Distribution of nodes and edges in the presence and absence of hair.

Table 6-22 ANOVA testing regarding the number of nodes and edges in the presence of hair.

	Degrees of freedom	Sum of squares	Mean square	F statistic	P value
Edges : Hair	1	5.1	5.135	0.206	0.651
Residuals	104	2594.3	24.945		
Nodes : Hair	1	5.7	5.669	0.397	0.53
Residuals	104	1485.4	14.283		

AIM 3: The effect of case specific conditions on vein network distribution.

This section addresses the effect of varying levels of image quality and the adjustment of hand position on the ability to observe vein network features from a digital image.

These conditions were considered to be representative of forensic case images, where no standardisation of images is presented. This section introduces analysis of the full dataset, to assess all variables (Table 5-5).

The effect of hand position

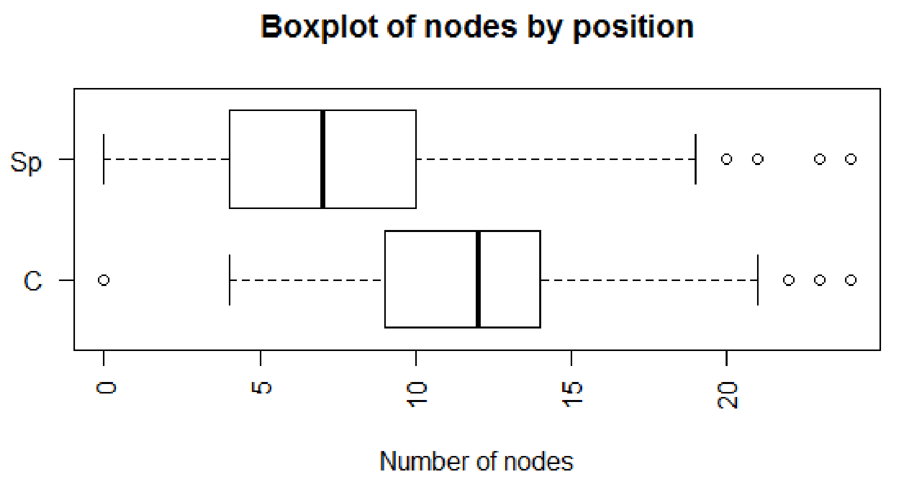
It was hypothesised that the clenched fist position (C), representing a standardised image with a clear view of the dorsum of the hand, would yield a more detailed recording of the vein network, and therefore a higher number of nodes and edges. Conversely, it was hypothesised that the semi-pronated position (Sp) would show a reduced number of features, as in this position a portion of the dorsum of the hand was not visible (the Sp view is common in forensic images).

Edges and nodes

This hypothesis was corroborated by the results, that show that the different hand position significantly affected the number of nodes and edges ($p = <0.001$) that were observed (Figure 6.38).

Due to the non-normality of the data, it was difficult to obtain robust statistical evidence for the hypothesis that hand position affects the ability to identify features; however the results show a strong indication of an effect.

The boxplots show that the median value of edges (Sp = 6, C = 11) and nodes (Sp = 7, C = 12) were higher in the C position, compared to the Sp position (Figure 6.38).



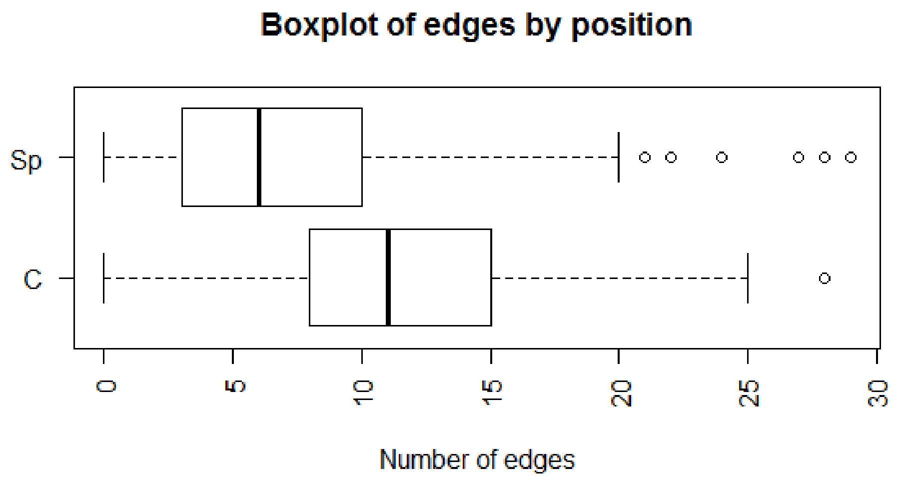


Figure 6.38 Number of edges and nodes by body side, Sp: semi-pronated, C: clenched fist.

Table 6-23 ANOVA results from tests on the number of edges and nodes, and the hand position.

	Degrees of freedom	**Sum of squares**	**Mean square**	**F statistic**	**P value**
Edges : Position	1	3020.	3020.4	110.7	<0.001
Residuals	634	17303	27.3		
Nodes : Position	1	2584	2584.2	132.6	<0.001
Residuals	634	12355	19.5		

Loops

The same hypothesis was tested with the number of loops. It was found that the C position consistently reported a higher number of loops than the Sp position (Figure 6.39).

The differences between position was explored further using Chi^2 testing. This was carried out on the data relating to 0, 1, 2 and 3 loops present only, as these data points exceeded the minimum value required for a feasible Chi^2 test. These results show the differences between the two positions was statistically significant (p = <0.001) (Table 6-24).

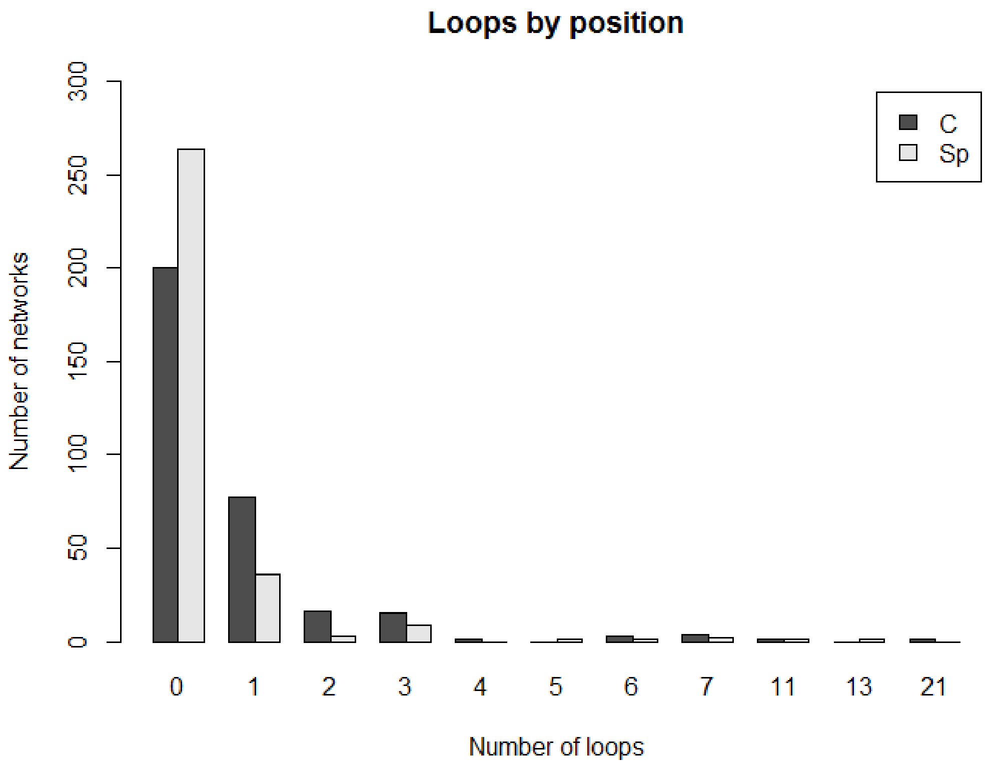


Figure 6.39 Total number of loops by position

Table 6-24 Chi^2 results regarding the number of loops identified in the two hand positions

		Clenched	**Semi-pronated**
Number of loops present	**0**	200	264
	1	77	36
	2	16	3
	3	15	9
Degrees of freedom		3	
χ^2 with Yates correction		34.074	
Critical value		7.815	
P value		<0.001	

Intersections

The same trend was seen with intersections (Figure 6.40). Chi^2 testing revealed that the differences in the two positions was statistically significant (p = <0.001) (Table 6-25).

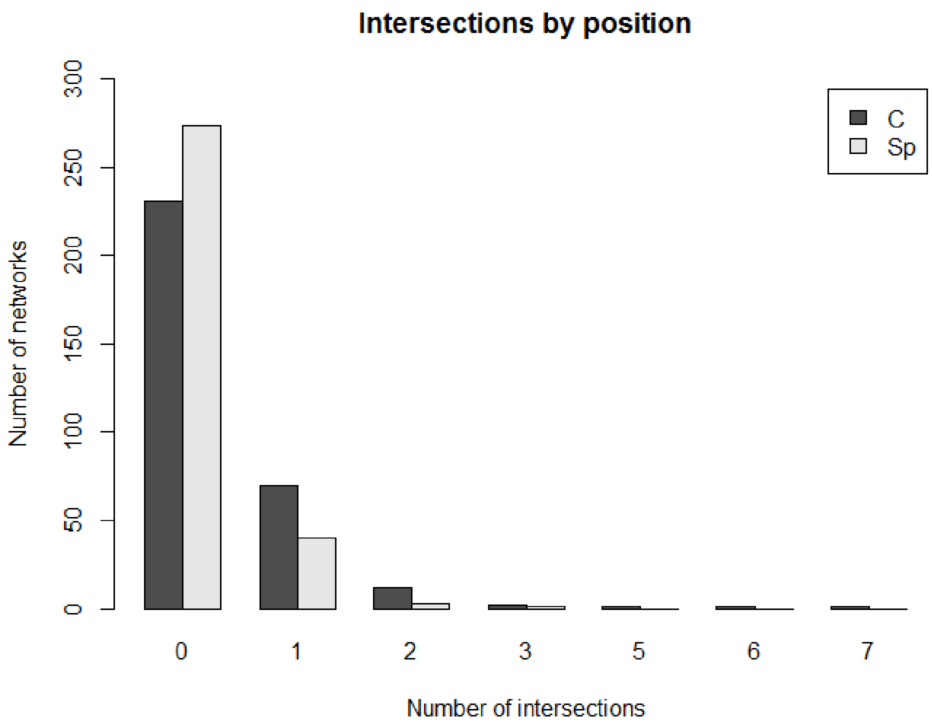


Figure 6.40 Total number of intersections by hand position

Table 6-25 Chi^2 results regarding the number of intersections identified in the two hand positions

		Clenched	**Semi-pronated**
Number of intersections present	**0**	231	274
	1	70	40
	2	12	3
Degrees of freedom		2	
χ^2 with Yates correction		17.2185	
Critical value		5.99	
P value		<0.001	

Motifs

When considering the identification of the motifs in the different hand position, the C position showed an increased number of each motif compared to the Sp position (Figure 6.41, Figure 6.42).

Figure 6.41 and Figure 6.42 shows all the 3 and 4 node undirected motifs identified on the database; these figures show that regardless of motif complexity, the C position consistently shows an increased number of motifs.

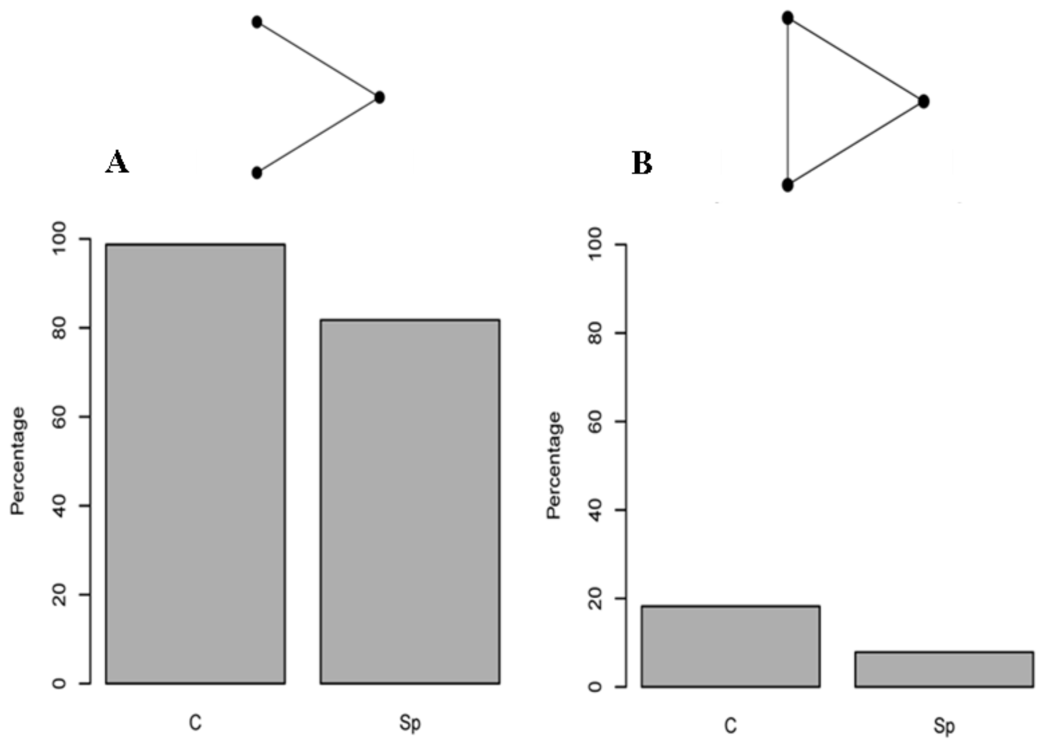


Figure 6.41 Distribution of 3 node motifs by hand position.

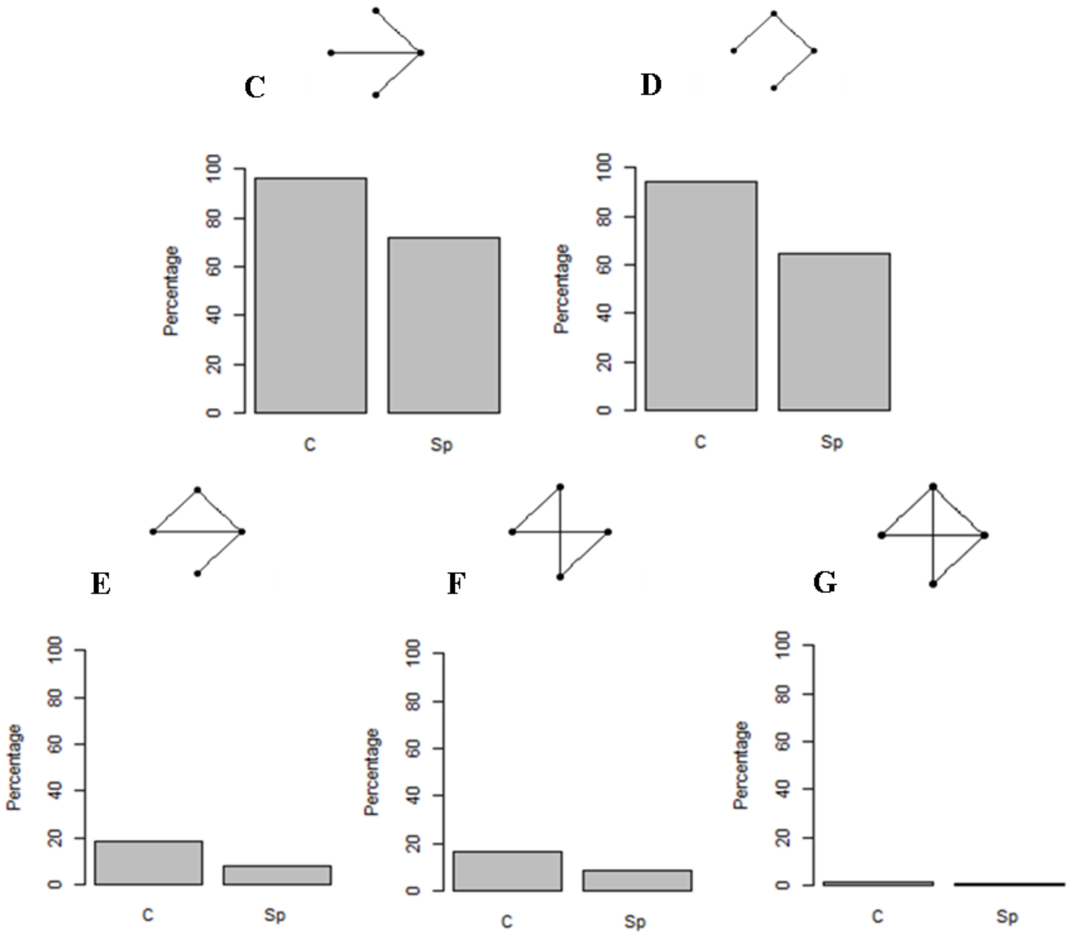


Figure 6.42 Distribution of 4 node motifs by hand position.

The percentage of motifs shown in the charts above should be interpreted with care, as they represent an over simplification of the data. Motifs are not considered in isolation, but instead considered as part of a larger structure, the network. Therefore part of one motif may contribute to part of another. It is for this reason that statistical analyses could not be conducted on this data. These graphs have been produced for illustrative purposes only.

The effect of image quality

It was hypothesised that varying image quality would affect the ability to observe the vein network features. It was hypothesised that as image quality declined, fewer features would be discernible.

Edges and nodes

This hypothesis was upheld by the results from the ANOVA testing; altering image quality significantly affected the number of edges ($p = <0.001$) and nodes ($p = <0.001$) that were observed (Figure 6.43).

The boxplots show that the median value of edges and nodes were consistently the highest in the 9 mp images, followed by the 0.3 mp images, with the lowest median number of edges and nodes present in the mobile phone (MP) images (Figure 6.43).

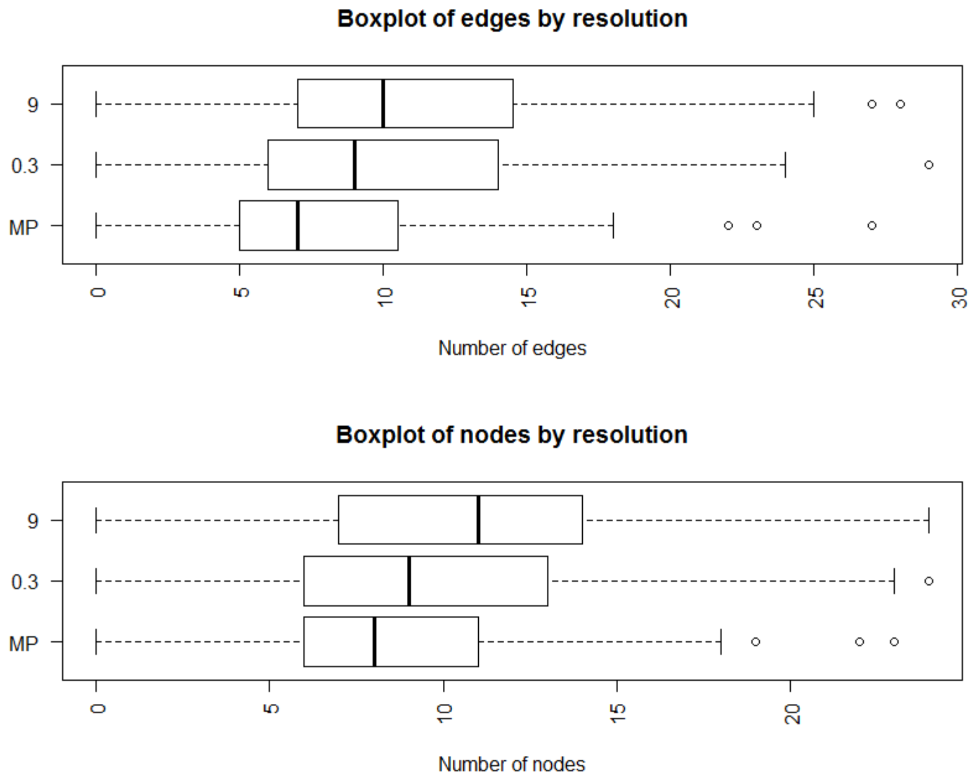


Figure 6.43 Number of edges and nodes by image quality. 9: highest quality, 0.3: medium quality, MP: lowest quality.

Table 6-26 ANOVA test results regarding the number of edges and image resolution.

	Degrees of freedom	Sum of squares	Mean square	F statistic	P value
Edges : resolution	2	993	496.7	16.27	<0.001
Residuals	633	19330	30.5		
Nodes : Resolution	2	599	299.57	13.22	<0.001
Residuals	633	14340	22.65		

Loops

The same trend was observed with the presence of loops; with the incidences of one loop present decreasing with each reduction in level of image quality (χ^2 =13.26 p = 0.039, Table 6-27). This trend changed when 2 or 3 loops were observed with the 0.3 mp images showing the highest prevalence, followed by the 9 mp, with the mobile phone showing the least number of loops (Figure 6.44).

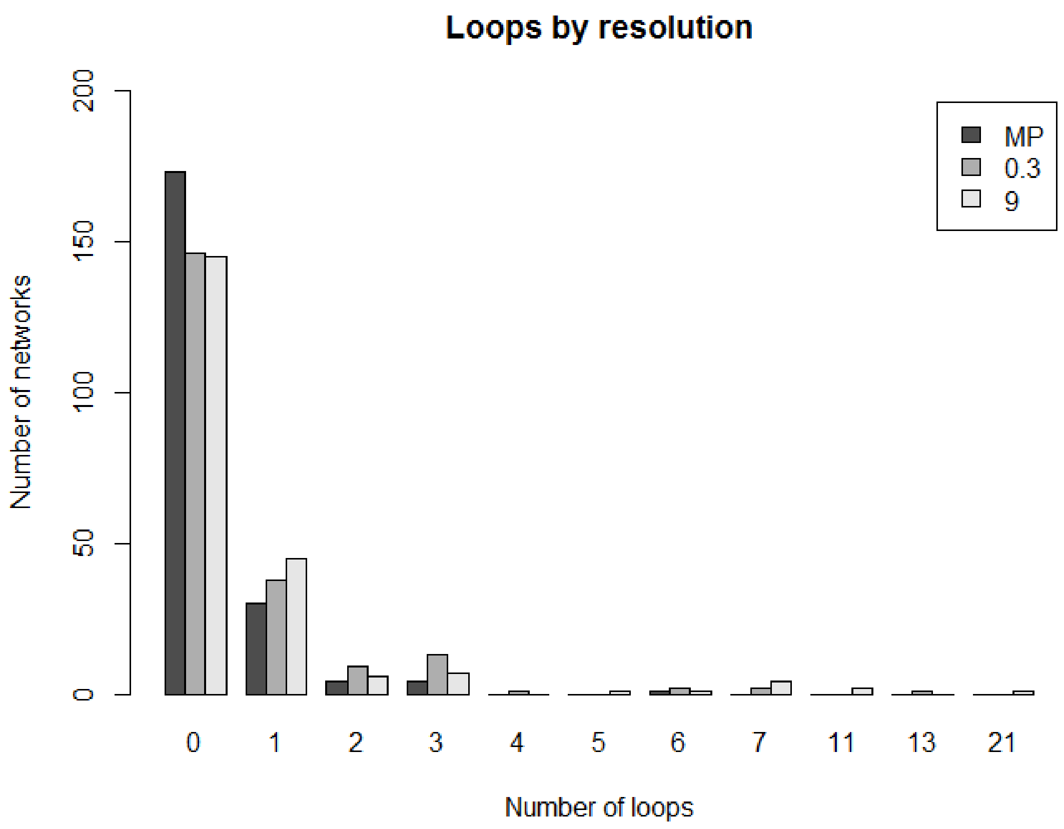


Figure 6.44 Total number of loops by image resolution

Table 6-27 Chi^2 results regarding the number of loops identified at different levels of resolution

		9 mp	0.3 mp	MP
Number of loops present	**0**	145	146	173
	1	45	38	30
	2	6	9	4
	3	7	13	4
Degrees of freedom		6		
χ^2 with Yates correction		13.26		
Critical value		12.59		
P value		0.039		

Intersections

As with loops, the presence of intersections were mostly observed in 9 mp, then 0.3 mp followed by the mobile phone images. However, cases of 2 intersections were more prevalent in the 0.3 mp than the 9 mp, but mobile phone remained the level of image quality with the least intersections present (Figure 6.45). The differences in resolution regarding the presence of intersections was shown to be statistically significant (χ^2 =15.43 p = 0.017, (Table 6-28).

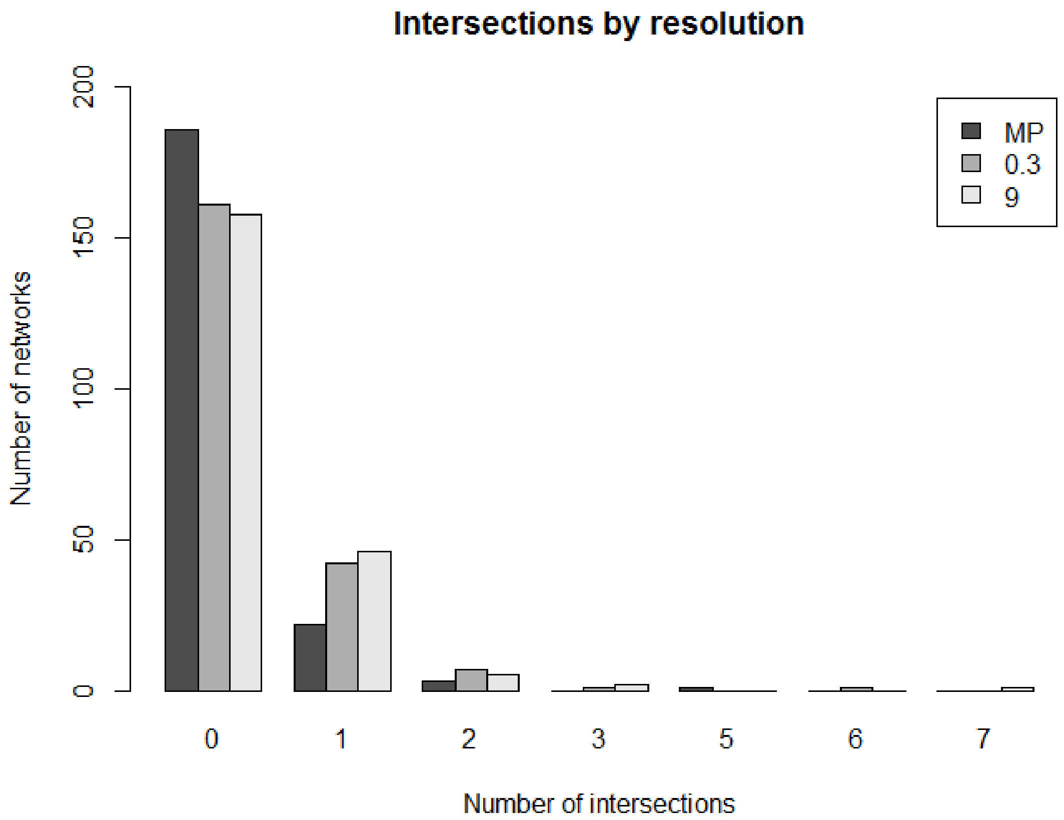


Figure 6.45 Total number of intersections by image resolution

Table 6-28 Chi^2 results regarding the number of intersections identified in different levels of image resolution

		9 mp	**0.3 mp**	**MP**
Number of intersections present	**0**	158	161	186
	1	46	42	22
	2	5	7	3
	3	2	1	0
Degrees of freedom		6		
χ^2 with Yates correction		15.43		
Critical value		12.59		
P value		0.074		

Motifs

Finally, the distribution of motifs across the levels of image quality was considered. For three motifs (ID 3) 9 mp images show the highest number of motifs, followed by the 0.3 mp, with the least seen in the mobile phone images. The 3 node loop (B) showed the same prevalence in the 9 mp and 0.3 mp, whereas the mobile phone images showed much less of this motif (Figure 6.46). For the 4 node motifs, the situation differed; either 9 mp > 0.3 mp > mobile phone (C and D), 9 mp = 0.3 mp > mobile phone was the case for motif E. In two cases (F and G), 0.3 mp has the highest number of these motifs present, followed by the 9 mp, and finally, the mobile phone showed the least (Figure 6.47).

As stated before, these charts are shown for illustrative purposes only, as statistical testing was not possible on this data.

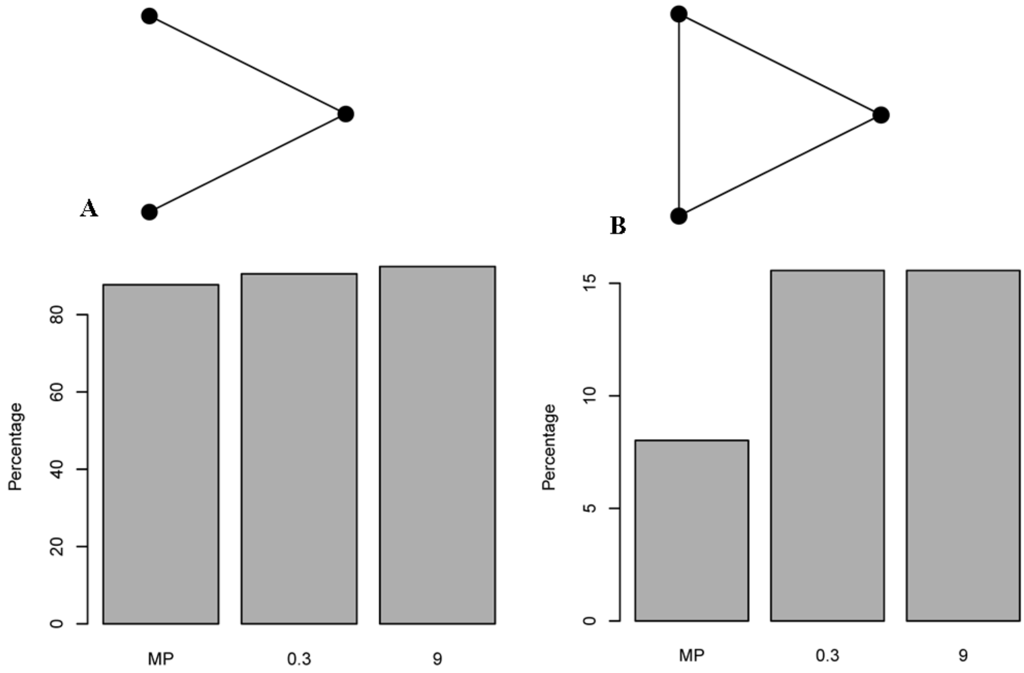


Figure 6.46 Three node motif distribution by image resolution

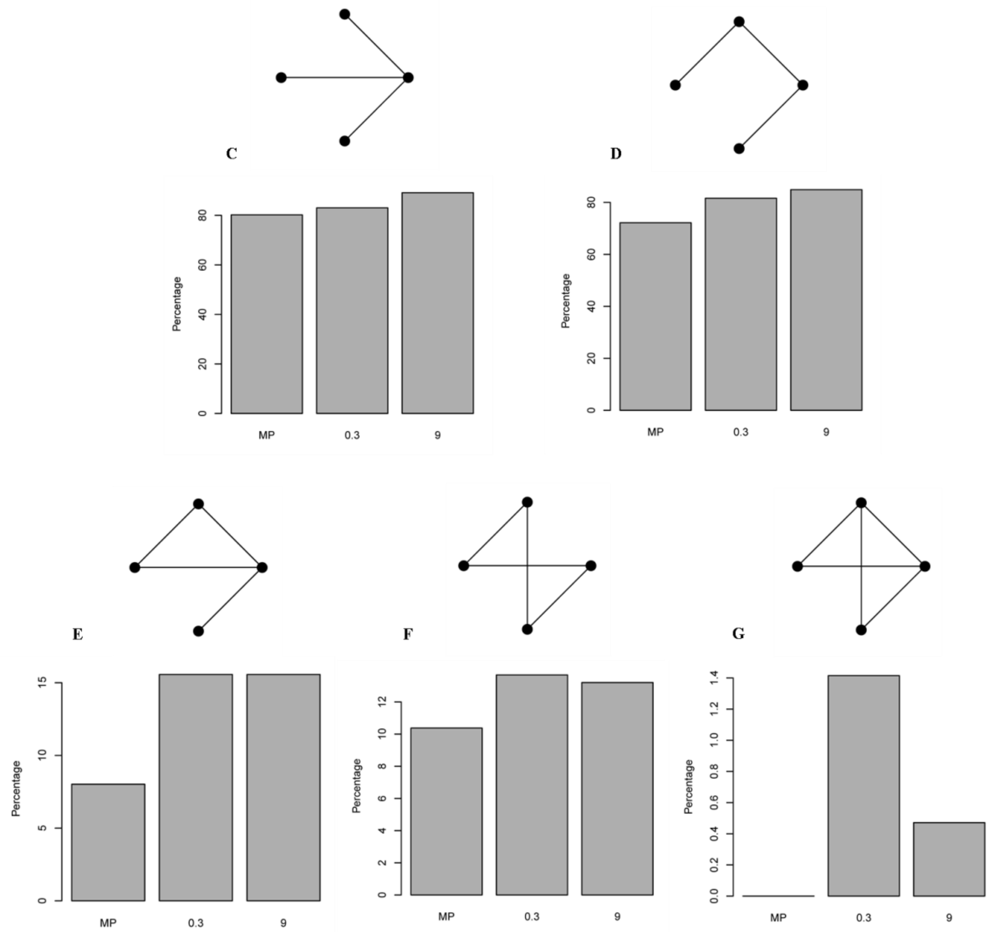


Figure 6.47 Four node motif distribution by image resolution

Considering all conditions

The results presented thus far have shown each imaging condition separately. This section will consider the combined effect of imaging quality and hand position.

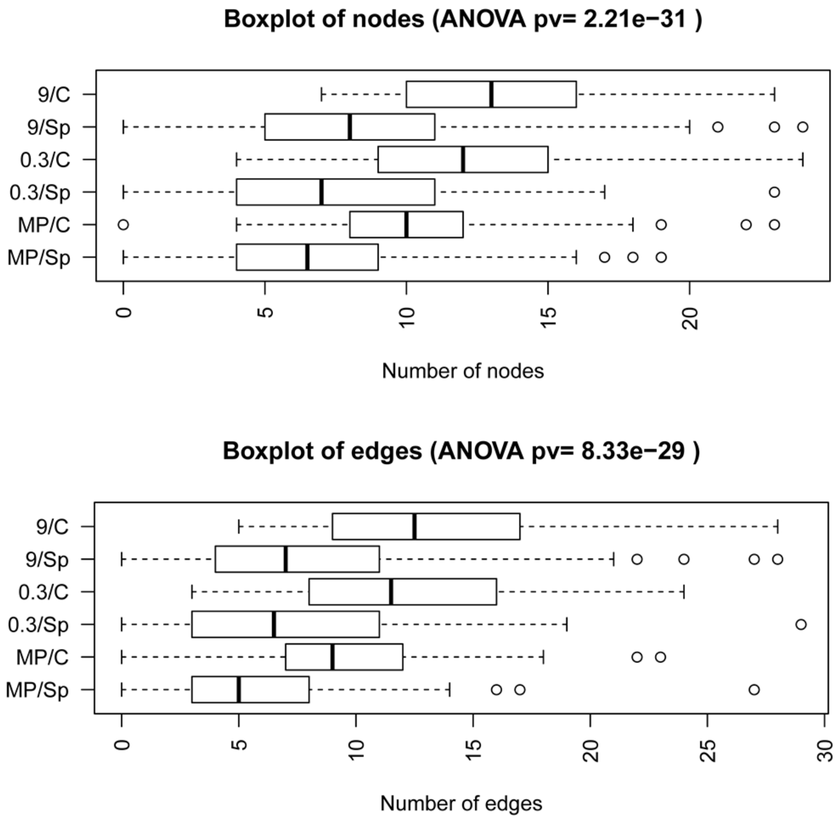


Figure 6.48 Number of edges and nodes in all combinations of imaging conditions.

Figure 6.48 shows the range of total number of edges and nodes found in each combination of imaging conditions. In this context, imaging condition relates to: image quality (9 mp, 0.3 mp, MP) * hand position (Sp, C). It can be seen that for both edges and nodes, the combination with the highest value is 9 mp in the C position. This value reduces as the resolution lowers (0.3 mp and mobile phone (MP)) but the hand position remains constant. Following this, is the highest resolution of the Sp hand position, again reducing as the resolution reduces but the position remains constant. Therefore the combination of conditions with the lowest number of vein network features identified was on the mobile phone in the semi-pronated hand position. This information is summarised in Table 6-29.

This shows that image quality is the most detrimental to the level of detail observed.

Table 6-29 Hierarchy of volume of vein feature information in all combinations of imaging conditions.

		Edges	**Nodes**
1	**Decreasing number of features observed** ↓	9 mp/Clenched fist	9 mp/Clenched fist
2		0.3 mp/Clenched fist	0.3 mp/Clenched fist
3		MP/Clenched fist	MP/Clenched fist
4		9 mp/Semi-pronated	9 mp/Semi-pronated
5		0.3 mp/ Semi-pronated	0.3 mp/ Semi-pronated
6		MP/ Semi-pronated	MP/ Semi-pronated

6.6.3 Vein pattern analysis, main study: discussion of results

Although a necessary step in the data collection process, it was decided that directional information would not be included in the thesis, for several reasons. Directional information was assigned in a subjective manner; this therefore invites some degree of unknown error. The non-directed data provides a sufficient overview of the vein networks without over complicating the situation, and for the scope of this thesis, was deemed appropriate. The directed information could be removed from the recorded data without revisiting the original images; therefore the directional data is available for future research.

AIM 1: Establish the variation of the vein network features.

It is important to be aware of the variation among vein pattern features to ascertain the discriminatory capability of the vein networks and their capacity to support the determination of an individual's identity. Knowing the range of variation will enable a better understanding of the expected level of variation between two individuals, when presented with this scenario in a forensic case.

To establish this, all known sources of variation were excluded to examine the variation in the vein networks in standardised conditions (9 mp, clenched fist data only).

Edge and node distribution

It was expected that the extremes of the range of vein patterns would be less prevalent and this was shown to be the case with regard to the number of edges and nodes. The majority of the networks on the 9 mp, clenched fist dataset were categorised as intermediate (8 – 16 edges, 9 -15 nodes) (Table 6-9). This information will be of value upon preliminary examination when presented with a vein network in a forensic case to establish where on the spectrum, the network exists; whether the network is typical (intermediate) or rare (extremes of the sample, sparse or dense).

For every edge there must be at least two nodes (start point and end point); so it may be assumed that the number of nodes should be at least double the number of edges. However this is not the case as some nodes comprise the start of one edge, but the end of another, whilst some nodes will possess multiple edges. It was found that the number of nodes and the number of edges are highly correlated (Table 6-11, Figure 6.19), and therefore both may be taken to represent the 'overall density' of a network.

It can be seen that three outliers exist; labelled A, B and C in Figure 6.19. Upon further investigation of these networks it was found that B and C contained a high number of loops with multiple loops it can be expected that the number of edges would be higher than the number of nodes, as loops often overlap, and 'share' nodes.

Edges

Edges (lines as they have been referred to in previous research) were shown to range from 5 to 28 across the sample, with a median of 12.5. Edges were found to be the most common feature by Aiken (2014) and Meadows (2011), who found the mean number of lines to be 12 or 13.25 (depending on the dataset used); to which the results from the current study are comparable.

Nodes

Nodes comprise several features in a vein network. They refer to the start or end points of edges, bifurcation points (a.k.a. branches (Meadows, 2011)), a point at which two edges intersect or a point where there is a change of direction.

The median number of nodes was 13, ranging from 6 to 24 across the sample. The number of nodes are useful in determining the overall 'density' of a vein network, but cannot be compared to other studies as nodes are a consequence of the chosen analysis method in the current study; network analysis has therefore not been reported elsewhere in the literature in relation to vein networks.

Motif distribution

Due to the fact that only undirected networks were considered, the number of motifs found from the dataset was 7. This consisted of 2, 3 node motifs and 5, 4 node motifs. Again, due to the lack of literature assessing vein networks in the way in which this has been performed in this study, there are no studies to which the current findings may be compared.

It is important to consider the prevalence of the motifs as these can inform forensic practitioners of the most commonly occurring topological arrangement of vein networks. For example, if a rare motif is observed, this would hold more discriminative capacity compared to a simple, 3 node motif.

Due to the small number of motifs identified it is unlikely that any motif will be discriminatory on its own. However, it would be interesting in future studies to assess the frequency of motif combinations. It is hypothesised that a combination of several motifs will offer increased discriminatory capability as opposed to the consideration of a single motif only.

Intersections

Previous studies have suggested that intersections are a relatively rare feature; Meadows (2011) found intersections in 10% of the sample, whereas Aiken (2014) found intersections in 42% of the NIR sample.

The current study found that intersections were present in 26% of the networks, a higher value than a previous comparable study (Meadows, 2011), which suggests they may not be as rare as first reported. It was most likely that only one intersection was present, although there were some cases where more than one intersection was observed.

It is important to know the prevalence of intersection when conducting a preliminary assessment of a vein pattern in a forensic scenario.

Loops

Based on previous studies it was hypothesised that loops were an uncommon feature within a vein network and therefore present as a potentially useful feature in terms of identification; Meadows (2011) found loops present in 23% of the individuals. Aiken (2014) found loops present in 70% of the sample, however this high incidence could be attributed to the fact that this data was extracted from NIR images, which are known to show more information regarding the vein pattern compared to visible light images (Meadows, 2011).

An understanding of the prevalence of loops is useful for the assessment of vein patterns in forensic cases. This study builds on previous research by defining the size of a loop, in terms of the number of nodes it possesses.

In the current study loops were found to be present in 40.6% of the networks. In networks that contained loops, there was most likely to be only one present (29.3% of networks), but in some cases there were several, with extreme cases showing 21 loops (<1% of the sample).

Loops comprising 3 nodes were the most common (one 3 node loop found in 16% of the networks) whilst larger loops were more rarely encountered (one 5 node loop found in 11.3% of networks) (Table 6-12).

This additional information is thought to be beneficial in forensic investigations as the presence of a loop may not be discriminatory in its own right, but the number of nodes it contains and the number of loops identified provides a more detailed description of the network, therefore likely providing more evidence for the discriminatory capacity of a network.

Complexity of networks

To explore the complexity of networks, beyond the number of nodes and edges, other features were also considered. It was thought that as the number of nodes and edges increases, the opportunity for more complex network arrangement would be likely.

Given the high correlation between the number of edges and nodes (Figure 6.19, Table 6-10) it was hypothesised that as these values increased, it would be more likely that a loop would be present, moreover that the number of loops would increase as node and edge numbers increased.

It was found that networks with loops present had a higher number of edges and nodes, however, the number of node and edges were not strongly correlated with the number of loops (Figure 6.29, Figure 6.30, Table 6-14). It can therefore be expected that a denser network in terms of edges and nodes is more likely to have a loop present, but cannot be assumed that it will have several loops.

The same trend was observed with intersections; when an intersection was present, it was more likely that the number of nodes and edges were higher, but the number of intersections was not strongly correlated with the number of nodes or edges (Figure 6.31, Figure 6.32, Table 6-16). Again the same inference can be drawn for intersections; a denser network is more likely to have an intersection, but will not necessarily have more intersections.

AIM 2: Influence of biological characteristics on the presence of vein network features

It was hypothesised that some biological features may affect the level of detail of a vein network that was visible from a digital image. Having an understanding of factors that affect the vein pattern would provide additional insight when assessing case information in a forensic investigation.

Effect of age

It was hypothesised that vein pattern features would not be influenced by the age of the individual. This was shown to be true; age was shown to be weakly correlated with the number of nodes or edges identified in vein networks (Table 6-17, Figure 6.33).

Effect of weight and body fat percentage

The weight and body fat percentage of individuals was measured to assess whether these may affect the level of vein pattern detailed observed. It is thought that individuals with a higher level of subcutaneous fat would show fewer vein network details as the superficial veins would be obscured by a layer of fat immediately superior to the network.

The weight of the individual was not correlated significantly with the number of nodes or edges (Table 6-18, Figure 6.34). Weight in kilograms informs of the overall weight of an individual, however it can be misleading as it does not consider the height of the individual as well as other factors (such as water content and bone mass), other than subcutaneous fat that can account for a person's weight. Body fat percentage was therefore measured as a more accurate indication of the amount of subcutaneous fat an individual possesses, and thus thought to provide a clearer indication of whether the individual's veins may be obscured.

A weak correlation was found between body fat percentage and the number of nodes ($p = 0.017$) and edges ($p = 0.042$), which was shown to be statistically significant (

Table 6-19). Although a weak correlation was found, it was statistically significant, giving these results more reliability than if it were not significant. Furthermore, the correlation between BF% and nodes/edges, although not strong, was stronger than the correlation between weight and nodes/edges.

Aiken (2014) also found that as body fat percentage increased, feature count decreased slightly, although this result was not statistically significant.

This information is important in a forensic scenario, as when presented with individuals of varying weight or fat %, it should not be assumed that the heavier the individuals, the less vein pattern will be discernible. However, what the current study and others have not considered is whether a change in the level of fat within an individual, affects the visibility of that individual’s veins. For example, if presented with an image that was captured a significant period of time before the forensic investigation, in which time the offender may have gained or lost weight, it cannot be known if that persons weight gain or loss will affect the level of pattern information seen which could potentially hinder the investigative process. To achieve this information, a study would have to be conducted using individuals who had lost or gained weight and assessing their vein patterns before and after (i.e. longitudinal as opposed to cross sectional study).

Effect of body side

The results from this research show that body side had no significant effect on the network density, in terms of the number of edges.

Previous studies have shown that the pattern of superficial veins between an individual’s left and right hands are asymmetric, but there was a suggestion that feature density may be similar within an individual (Meadows, 2011).

Forensic practitioners use the method of mirror imaging hand images when comparing suspect and offender images (Meadows, 2011). This is performed to assess a pseudo-left hand and a real left hand, and in cases where there are many similarities in suspect and offender images, this can support the argument that there are more differences between an individual's own left and right hands than there are between the suspect and offender images.

Body hair and obscured region of interest

Body hair, although not considered as a 'stand-alone' feature, was considered for its potential effect on the ability to visualise structures on the dorsum of the hand, as it has been suggested that hair coverage can obscure the vein pattern (Lingyu and Leedham, 2006; Paquit et al., 2007). It was hypothesised that with extensive hair coverage, other anatomical structures might be obscured including the vein network. However, hair was not found to have a significant effect on the number of nodes or edges recorded.

In the current study, hair was recorded as present or absent, which did not account for the extent of hair coverage. Future studies would benefit from a scale with regards to hair coverage could explore this further to examine how different levels of coverage affect the ability to identify vein pattern features.

AIM 3: To determine the effect of case specific conditions on vein network distribution.

This section set out to address the effect of varying levels of image quality and the adjustment of hand position, on the ability to observe vein network features in a digital image.

Currently, it is accepted that the majority of suspect images will be of higher quality than offender images, although the extent to which they differ has not been quantified.

It was hypothesised that the standardised images, representing the images taken in police custody, to which the offender images are compared, would hold more information regarding vein patterns, compared to the images chosen to represent the offending images (lower image resolution and non-standardised hand position).

The effect of hand position

Two hand positions were examined; C to represent an ideal, clear view of the dorsum of the hand; also because this position has been shown to reduce tendon interference, which can affect the visualisation of veins, by causing shadows which can be misidentified as veins (Bellini, 2010). The non-ideal hand position was selected to show the hand in a functional position; a position chosen as it is often observed in forensic case images; Sp position. In some circumstances, the suspect can be instructed to position their hand in the same positon as seen in the offending image; however this does not always transpire and can be difficult to control.

Edges and nodes

The difference in the level of detail observed between the Sp position and the C position was shown to be statistically significant for the number of nodes and edges ($p = <0.001$). The highly significant values indicate an effect was present, however as the data was not normally distributed, it is difficult to deduce as to whether this result can be relied.

Loops and intersections

When assessing the complex structures of a vein pattern, more loops were found in the clenched position compared to the Sp position. Chi^2 testing reveals that both structures were significantly more prevalent in the C position that the Sp (Table 6-24, Table 6-25).

A study by Khan and Khan (2014) showed that slight deviations in the orientation of the hand do not affect the detail of pattern observed greatly, however deviations of more than 10° significantly reduced the ability to observe pattern details.

A recent study carried out by Donnelly (2014) found that the least pattern dense region on the dorsum of the hand was the lateral region, encompassing the proximal thumb to the anatomical snuffbox. This region is prominently observed in the Sp position; therefore the current research findings are comparable to the finding of Donnelly (2014).

In relation to the anatomy in this region, the lateral portion of the dorsum of the hand is predominantly soft tissue, whereas the central and medial portion of the hand comprises the bony tissue. Based on the results from this research and by Donnelly (2014) it is postulated that the veins are more readily visible when laying over the bony structures than compared to when a more muscular base is present.

The effect of image quality

Three settings of image quality were examined for the level of vein pattern detail that could be extracted from each; a Fujifilm DSLR at 9 mp, at 0.3 mp, and a Blackberry Bold 9700 mobile phone camera. The Fujifilm DLSR 9 mp images were selected to represent the custody suite images, whilst 0.3 mp images and images taken on a mobile phone were chosen to represent the offender images.

It was expected that the 9 mp DSLR images would have the most information relating to vein networks, followed by the 0.3 mp DSLR, and the mobile phone was expected to have the least information detail.

Edges and nodes

This was shown to be true regarding the number of edges and nodes (Table 6-26) identified and when one loop (Table 6-27) or intersection (Table 6-28) was observed. However, when 2 loops or intersections were observed, the 0.3 mp images showed a higher incidence than that 9 mp, although the differences were minor (). The mobile phone images consistently illustrated the least pattern information.

Due to the non-normality of the data, it was difficult to assess the statistical validity of the hypothesis; however the results show a strong indication of an effect.

This information is of value to the forensic practitioner when assessing and reporting on images of carrying quality (resolution). This data will enable the practitioner to report the estimated loss of detail in a quantified manned, and therefore be able to account for some differences observed between suspect and offender images.

Considering all conditions

Each of the imaging conditions (hand position: clenched and semi-pronated, image quality: 9 mp, 0.3 mp and mobile phone images) were considered in isolation before being considered cumulatively. It was found that for both edges and nodes, the combination with the highest value was 9 mp in the C position. The number of nodes and edges reduces as the resolution lowers (0.3 mp then mobile phone) but the hand position remains constant. Following this, is the highest resolution of the Sp hand position, again reducing as the resolution reduces but the position remains constant. The combination of conditions with the lowest number of vein network features identified was on the mobile phone in the semi-pronated hand position.

These observations may be obvious; however the clarification of these observations from a suitable database is important to qualify when presented with this situation in a forensic scenario, to meet admissibility requirements,

Main study overall discussion

It is clear that some vein network features are more prevalent than others, and therefore some features provide more discriminate support. However, it is suggested that the exact combination of features within a vein network will be more discriminatory than considering the features in isolation. It is proposed that future studies consider the likelihood of certain features occurring together to heighten the discriminatory capacity of the vein network as an identifiable feature; thus considering the network as a whole, rather than individual features.

The assessment of isolated motifs in particular is a simplified method, chosen for the purposes of this thesis to provide an overview of vein network variation. However, in reality these features do not occur as isolated features, instead they act as part of a larger structure and should be considered in this manner.

The benefit of this research is that the results presented will provide the forensic practitioner with quantified data which can be used to aid reporting of the difference and similarities between suspect and offender images. Currently, information loss due to differing image quality is stated as a potential reason to explain some of the differences between two images; the results from this study will provide support for this type of claim; however more statistical analyses are required to enable the reporting of how much information loss can be expected between two sets of images of different quality. This enhanced level of reporting will add to the robustness of the presented evidence in that empirical research can be relied on.

7 ANATOMICAL SURFACE FEATURES STUDY

In addition to the superficial vein pattern as a method of identification in forensic cases, this thesis illustrates that anatomical surface features are also useful to aid in the investigation of alleged child sexual abuse, where aspects of anatomy are used to establish similarities and differences between two individuals. These features can be assessed by forensic experts to build a profile of an individual based on the anatomical features that can be seen in a digital image (Black et al., 2014a). This section establishes the discriminatory capability of anatomical surface features on the dorsum of the hand as an aid to human identification through the comparison of anatomy.

A review of casework performed by forensic experts at CAHId indicates that the most common features used in these circumstances are areas of isolated pigmentation (including, but not restricted to melanocytic nevi and ephelides), and areas of scarring or injury[3] (Figure 3.16).

In this study, hair was also considered as a potential factor in affecting the visibility of pigmentation and scars; it was hypothesised that the presence of hair may obstruct other features, and therefore hinders the ability to visualise them.

This section presents the results pertaining to the following aims:

1) To determine the reliability and repeatability of the method of extracting surface feature information, to establish validity of the chosen method;
2) To determine the extent of surface feature variation in the sample population;
3) To investigate the influence of biological characteristics on the ability to visually identify the surface features;
4) To investigate how robust the surface features are when assessed in an image of poor quality (representative of a forensic case image), compared to a standardised image (representative of a suspect image taken in custody).

[3] These are the most common features used on the dorsum of the hand in the C or Sp position; does not consider features that can be observed when the fingers are extended i.e. knuckle creases and nail bed features.

7.1 Material and methods

7.1.1 Description of the images

Images were extracted from the Vein Pattern Project (VPP) database (see section 5.3, Table 5-5), and visually assessed to determine whether the aforementioned anatomical surface features were present. Images were examined from 53 male individuals, with an age range of 18 to 39 years (mean 22.8 years).

To reiterate section 5.3, the images in question were taken at three levels of quality; Fujifilm IS-1 camera at 9 megapixels (mp) (high), at 0.3 mp (medium), and on a Blackberry Bold 9700 camera phone (low). Images were taken from two hand positions; clenched fist and semi-pronated from both the left and right hands. This resulted in 12 images per individual (636 images total) (Table 5-5).

7.1.2 Data extraction

Image files were opened and assessed in Adobe® Photoshop®. In some images, the hue and saturation levels were adjusted to enhance the appearance of the features. This was performed using the 'Adjustments' tab from the toolbar in Adobe® Photoshop® and adjusting the slider on the Hue and Saturation tabs. In the cases where these settings were adjusted, the values were recorded for future reference.

Information relating to the presence of the features was recorded in an Excel spreadsheet, in a binary format; '0' if the feature was absent, '1' if the feature was present (Table 7-1).

Table 7-1 Excerpt from the recording sheet for anatomical surface feature data. URN: reference number of individual in the image; Date: date of image assessment; Pigmentation, Scars, Hair: data relating to each feature; Hue, Sat: hue and saturation levels if adjusted.

URN	Date	Pigmentation	Scars	Hair	Hue	Sat
004	21.09.13	0	0	1	0	0
008	21.09.13	0	1	0	0	19
012	21.09.13	0	0	0	0	16

7.1.3 Data analysis

All analysis was carried out in R (version 3.1.1, R Development Core Team 2014). All data input and coding was performed R Studio©; the interface for R.

Several methods of data analysis were required to accommodate for different types of data. In all cases there were binary (categorical) variables for data relating to the presence or absence of features. In the main dataset, the presence of the features was assessed in conjunction with biological characteristics, some of which comprised variables that were classified as continuous; e.g. age, weight, body fat percentage.

Analysis of Variance

One-way analysis of variance (ANOVA) was used where explanatory variables were categorical and response variables were continuous.

ANOVA is a parametric method that tests the hypothesis that two (or more) samples have the same mean and variance. ANOVA assumes that the data are normally distributed, that the variances in the experimental conditions are similar, and that the observations are independent (Field, 2009). During this study normality was tested by producing and assessing quantile-quantile (Q-Q) plots in R. These plots rank samples from the data against a similar number of ranked quantiles (subsets of the data taken at random intervals) from a normal distribution; if the sample is normal, the line is straight. If there are any departures from normality, the line will not be straight and can appear in a variety of shapes (Crawley, 2013). These plots will only be discussed where a departure from normality was observed.

The output from an ANOVA will report whether the differences between the two groups are significant. The 'F' value is the ratio of the variation explained by the model, to the variation not explained by the model (the residual error variation). If this value is less than one, the variation in the model is not likely to be significant. If the value is greater than one, this indicates that the experimental manipulation had some effect, above what would have been expected from the individual differences (Field, 2009). The ‘p’ value is the probability that the results obtained could have occurred by chance, and therefore when this value is low (by convention ≤ 0.05), it indicates a statistically significant result.

Generalised linear modelling was also carried out on some elements of the data, but in all cases the models contained a substantial level of unexplained variance and high residual deviances. It was not possible to reduce this with the explanatory variables available, and therefore this aspect of the modelling process was deemed unsatisfactory for inclusion in the thesis.

Pearson’s Chi Squared (Chi^2)

Pearson’s Chi^2 tests were used when all the data was categorical, to test whether an association between two variables was present (Field, 2009).

The relevant raw data was arranged into contingency tables. A contingency table shows the number of observations, or observed frequencies, for two or more categorical variables, arranged in a grid; the number of each observation for each variable appearing in the cells of the grid (Field, 2009).

Pearson’s Chi^2 test assesses the significance of differences between the observed and expected frequencies, therefore testing the independence of the two categorical variables, by calculating the sum of the observed frequency (O) minus the expected frequency (E) squared, and divided by the expected frequencies (Equation 1) (Crawley, 2005; Crawley, 2013).

Equation 7-1: $\chi^2 = \sum (O - E)^2 / E$

In R, the default for this test is for the application of Yate's correction, which adjusts the observed frequencies by adding or subtracting 0.5 (Sokal and Rohlf, 1995), thereby lowering the value of Chi^2, making it less significant (Field, 2009). It is used to avoid the accidental identification of an effect where one does not really exist, which is predominantly utilised when expected frequencies fall below 5. There is some argument over the use of Yate's correction; some sources state that it should be used on all 2 x 2 contingency tables (Field, 2009; Howell, 2013), whereas others have stated it is unnecessary to use with small samples (n = <20) (Sokal and Rohlf, 1995).

All Pearson's Chi^2 analyses were carried out with and without Yate's correction to check for difference in the output. Only where a discrepancy occurred will both sets of results be discussed.

To determine acceptance or rejection of the null hypothesis based on the Pearson's Chi^2 test statistic, the critical value was established. If the calculated value of the test statistic was greater than the critical value of the distribution for the relevant degrees of freedom, the null hypothesis was rejected (Crawley, 2005). Conversely, if the value of the test statistic was less than the critical value, the null hypothesis was accepted.

An assumption of Pearson's Chi^2 is that the expected frequencies will be greater than five. In cases of low expected frequencies there will be a loss in statistical power and the test may fail to detect a genuine effect (Field, 2009). The low expected values inflate the test statistic and therefore it can no longer be assumed to follow the Chi^2 distribution. During this study, in cases where there were low numbers of observed frequencies, the Pearson's Chi^2 approach was not sufficiently robust to deal with the low values, therefore Fishers exact test was used.

7.2 Observer reliability study

This section will present the results from the observer reliability tests. For the method of image analysis and data extraction to be viable, the results must be proven repeatable on more than one occasion and by more than one individual.

7.2.1 Intra-observer repeatability

Intra-observer repeatability indicates the ability of one observer (the author) to achieve the same result on more than one occasion, thus indicating the repeatability of one individual's performance of the prescribed methods.

Methods

30 images of the dorsum of the hand in a clenched fist position were selected at random from the VPP database. These images were from 15 individuals, including both the left and right hands (full raw data in appendix K).

The images were examined 8 times, following the methodology described in section 0, leaving at least 24 hours between repeats to avoid image memory bias.

The raw data for each feature group recorded in the Excel spreadsheet was combined and stacked in Excel before being organised into contingency tables in preparation for analysis in R, using Pearson's Chi^2 to allow the results between repeats to be assessed.

Results

Results will be presented for each surface feature in turn.

Pigmentation

There was no significant association between the different repeats and the presence or absence of visible pigmentation (χ^2 = 0.6, critical value = 14.07, p = 0.99) (Table 7-3).

Figure 7.1 illustrates this result, showing that in repetition 2 only, was the recorded presence of pigmentation different from all other repeats. This equates to an agreement rate of 87.5%, suggesting that the identification of pigmentation was repeatable.

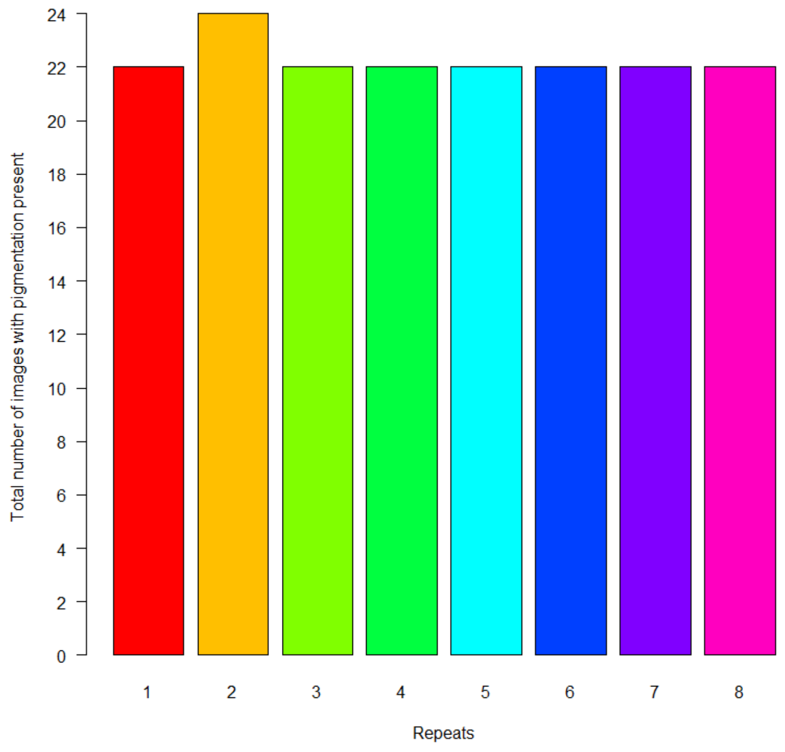


Figure 7.1 Number of images with observed areas of pigmentation, for all 8 repeats

Scars

Figure 7.2 highlights a range of observations made across the 8 repeats with regard to the presence of scars. This ranges from scars being identified in 8 images, to 15 images. Despite the apparent fluctuations in the observed frequencies, there was no significant association between the different repeats and the presence or absence of visible scars (χ^2 = 6.9, critical value = 14.07, p = 0.43) (Table 7-3).

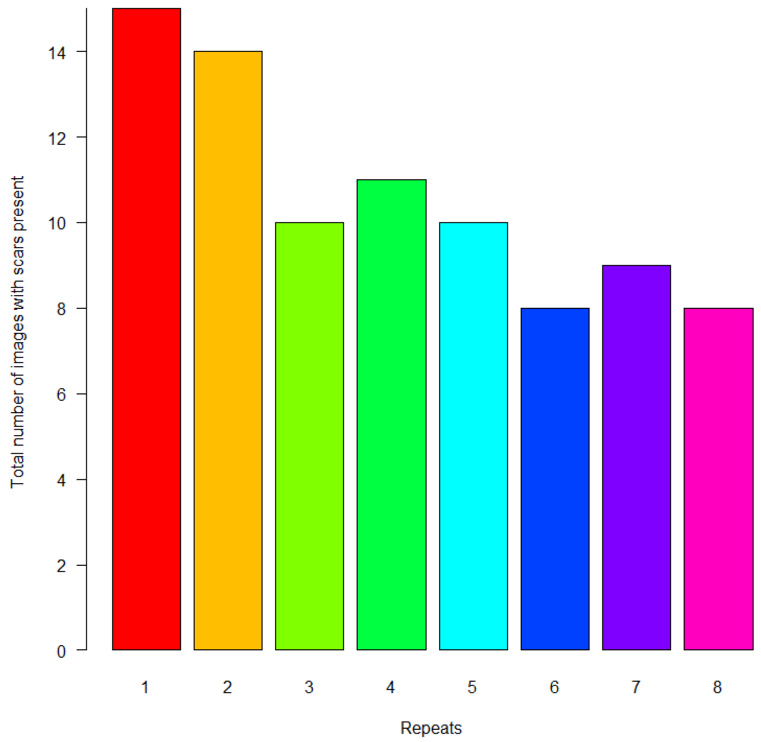


Figure 7.2 Number of images with observed scars across all 8 repeats

Despite no significant relationship, Figure 7.2 highlights an interesting trend from the scar data, whereby no 2 repeats observed the same number of images with scars present, and it appears that scar observation decreases throughout the study; most were observed in at the start of the study, with the least observed at the end of the study. Further tests were conducted to examine whether any significant differences existed between the 8 repeats with regard to recorded data for scars; p values from the Chi2 tests are tabulated for each interaction (Table 7-2).

Table 7-2 p values from Chi^2 testing between each repeat with regard to the presence of scars.

		Repeats							
Repeats		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	1	0	0.853	0.317	0.433	0.317	0.144	0.221	0.144
	2		0	0.414	0.549	0.414	0.201	0.297	0.201
	3			0	0.827	1	0.637	0.819	0.637
	4				0	0.827	0.491	0.655	0.491
	5					0	0.637	0.819	0.637
	6						0	0.808	1
	7							0	0.808
	8								0

Table 7-2 shows that no statistically significant interactions were found between any of the repeats, despite the apparent trend in Figure 7.2. In all cases the value of Chi^2 did not exceed the critical value, and therefore the null hypothesis was accepted, that there were no statistically significant differences between repeats.

Hair

Figure 7.3 highlights the range of observations made across the 8 repeats with regard to the presence of hair. In 3 repeats, the observer identified 24 images with hair; in another 3 repetitions, 25 images were identified as having hair and in 2 further repeats found 26 images with visible hair.

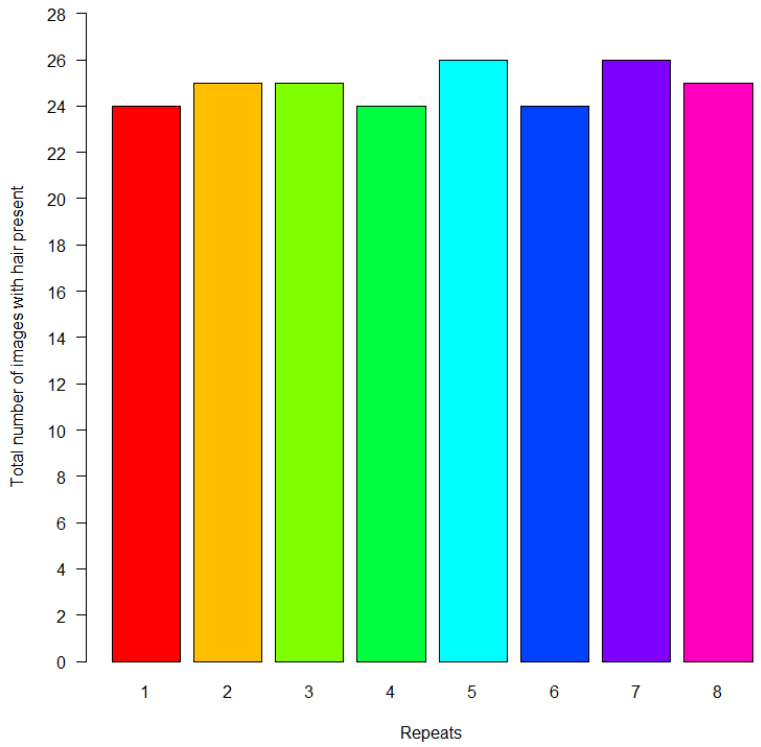


Figure 7.3 Number of images with observed hair across all 8 repeats.

The Chi^2 testing showed that there was no significant difference between the repeats and the presence or absence of visible hair on the dorsum of the hand ($\chi 2 = 1.15$, critical value = 14.07, $p = 0.99$) (Table 7-3).

For all surface features it was found that, there were no statistically significant differences in the recorded presence across all 8 repeats. This data is summarised in Table 7-3.

Table 7-3 Summary of results from Chi^2 tests for all surface features from the intra-observer study.

Feature	**Chi ^{2} value**	**Critical value**	**P value**
Pigmentation	0.6	14.07	0.99
Scars	6.9	14.07	0.43
Hair	1.15	14.07	0.99

7.2.2 Inter-observer reliability

Inter-observer reliability is a means of testing whether the same result can be achieved by more than one individual (Table 7-5).

Methods

Four observers were recruited for their varying level of expertise in hand image analysis in forensic investigations and anatomical knowledge.

- Observer A had anatomical knowledge, but no experience of examining digital images of the dorsum of the hand, for either forensic or research purposes.
- Observer B had no anatomical knowledge, and no experience of examining images of the dorsum of the hand for either forensic or research purposes.
- Observer C had extensive anatomical knowledge of the dorsum of the hand and extensive experience in forensic investigations involving the examination of the dorsum of the hand for identifiable features.
- Observer D had anatomical knowledge of the dorsum of the hand, and some experience examining database images of the dorsum of the hand with specific focus on the anatomical features used in forensic investigations.

Table 7-4 Summary of observer experiences

Observer	**Anatomical knowledge**	**Experience of hand image analysis**	**Forensic experience in image analysis**
A	✓	✗	✗
B	✗	✗	✗
C	✓	✓	✓
D	✓	✓	✗

Observers were provided with instructions (Appendix L), which followed the same methods as described in section 0, and the same set of images as the intra-observer study (30 images of the dorsum of the hand in a clenched fist position, from 15 individuals, left and right hands).

The raw data recorded in the Excel spreadsheet from each observer was combined, stacked and organised into contingency tables in preparation for analysis in R Studio using Pearson's Chi^2 tests (Appendix M). In cases where there were low expected frequencies, Fishers exact test was performed (section 5.1.3).

Results

Pigmentation

There was no significant association between the different observers and the presence or absence of visible pigmentation (χ^2 = 1.02, critical value = 7.8, p = 0.80) (Table 7-6).

Figure 7.4 shows the minimal variation in recorded presence of areas of pigmentation across the four observers. It shows that observers B and C agreed on the number of images that contained isolated areas of pigmentation, whereas observers A and D differed in their opinion, both from one another and from observers B and C.

Observers B and C differed in their level of experience and knowledge, indicating that these factors may not influence the ability to reproduce the same result.

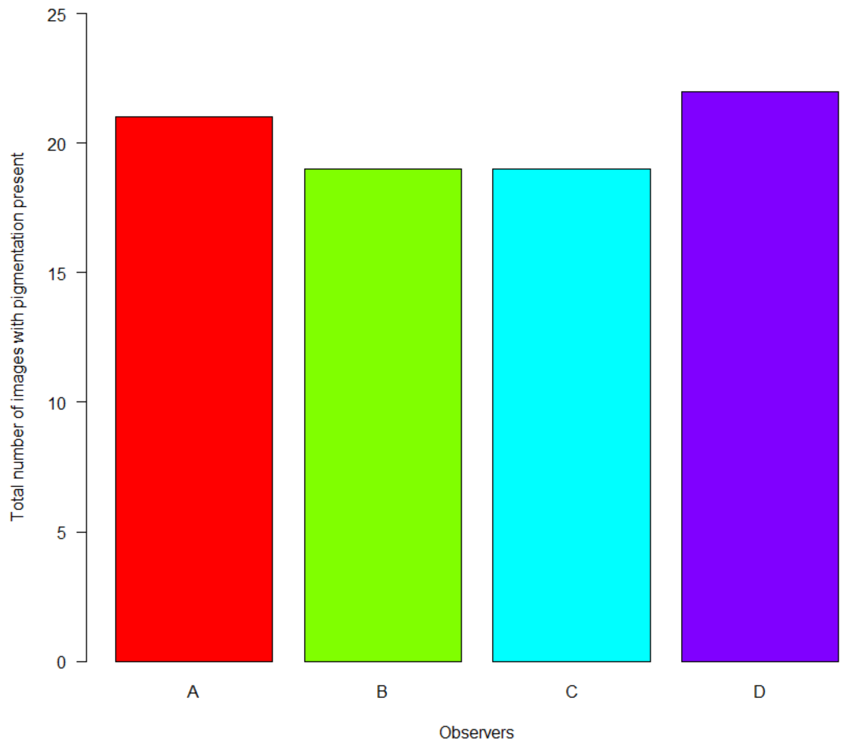


Figure 7.4 Observed frequencies for areas of isolated pigmentation from the 4 observers.

Scars

There was no significant association between the recorded frequencies of scars and the different observers ($\chi^2 = 5.5$, critical value = 7.8, p = 0.14) (Table 7-6).

Due to some of the expected frequencies having a value of less than five, it was necessary to run a Fishers exact test on this data. The resulting p value was marginally higher than that from the Pearson's Chi^2 tests (p = 0.17), reaffirming that no association exists between the recorded presence of scars and different observers.

Despite this, Figure 7.5 shows that none of the observers agreed on the number of images containing scars, suggesting that the repeated identification of scars is less robust than of pigmentation.

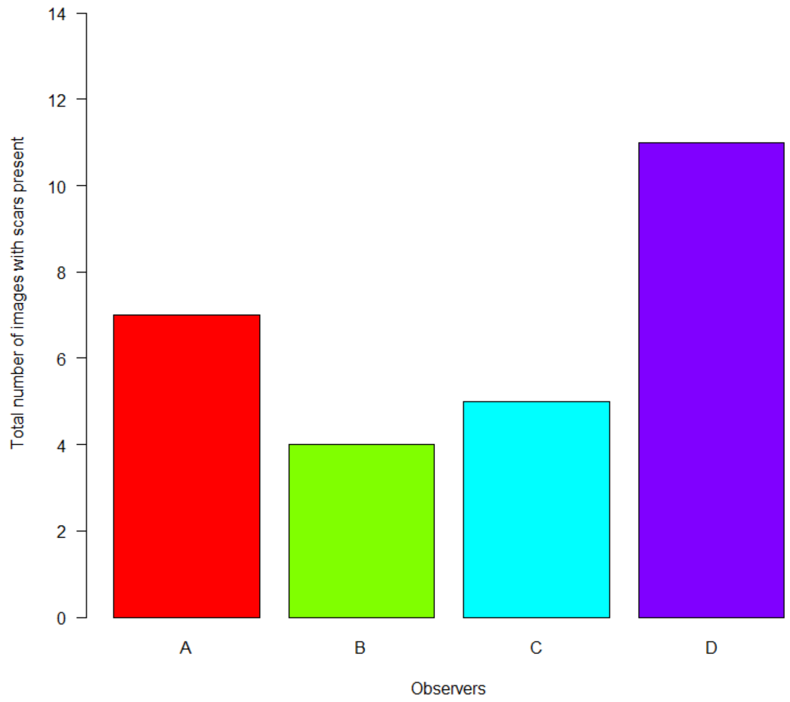


Figure 7.5 Observed frequencies for scars from the 4 observers.

To explore this trend further Chi^2 tests were conducted between all observers, the p values from these tests are listed in Table 7-5. Observers B and D differed in their anatomical knowledge and experience of hand analysis, but shared a lack of forensic image analysis experience. It can be seen that there were no cases where the differences in recorded presence of surface features were statistically significant. However, it should be noted that between observer B and D, the differences were close to the critical value for Chi^2, and the p value close to statistical significance.

Table 7-5 p values from Chi^2 testing between each observer for scar observation.

		Observers			
		A	**B**	**C**	**D**
Observers	**A**	0	0.366	0.564	0.346
	B		0	0.739	0.071*
	C			0	0.134
	D				0

Hair

There was no significant association between the recorded number of images with hair present and the different observers (χ^2 = 4.4, critical value = 7.8, p = 0.22) (Table 7-6). Due to some of the expected frequencies having a value of less than five, it was necessary to run a Fishers exact test on this data. The resulting p value also showed that there was no significant association between hair identification and the different observers (p = 0.23).

Figure 7.6 shows that observers A and D agreed on the number of images containing hair. Both A and D have anatomical knowledge, but differed in their experience of examining the dorsum of the hands for identification purposes.

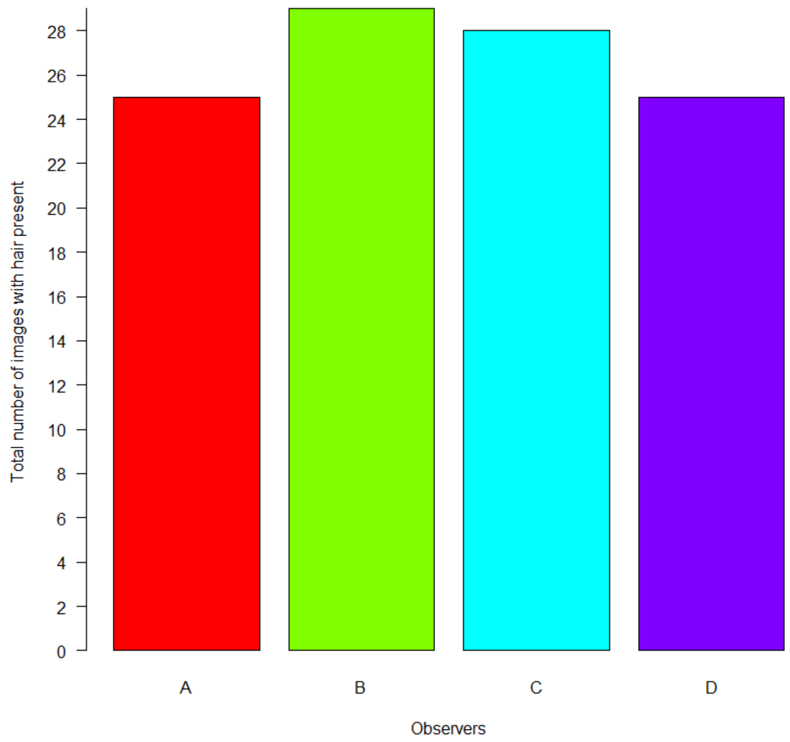


Figure 7.6 Observed frequencies for hair from the 4 observers.

All Chi^2 test results for the inter-observer study are summarised in Table 7-6.

Table 7-6 Summary of results from Chi^2 tests for all surface features from the inter-observer study

Feature	**Chi^2 value**	**Critical value**	**P value**	**Fishers exact test: p value**
Pigmentation	1.02	7.8	0.80	n/a
Scars	5.5	7.8	0.14	0.17
Hair	4.4	7.8	0.22	0.23

7.2.3 Observer reliability study discussion of results

Observer reliability studies are an important aspect of developing a forensic technique (Dror *et al.*, 2006; National Research Council of the National Academies, 2009; Page *et al.*, 2012). The results from these studies therefore go some way towards addressing this issue by indicating that identifying surface features on the dorsum of the hand from digital images is repeatable both by one observer and by several.

It should be noted that in the intra and inter-observer studies caution should be upheld in interpreting results as it is not possible to determine whether the same area of pigmentation or scar was recorded each time. Identification of surface features was simplified to the recording of the presence or absence of features only, as the location has been investigated in previous studies (Macdonald-McMillan, 2011), furthermore, for the purposes of this study, presence and absence information was sufficient.

Primarily, the purpose of collecting surface feature information for this research was to allow its use in conjunction with the vein pattern information, therefore precise detail regarding location, orientation, size and exact physiological description was out of the remit of this research. It is important to note however, that precise location and additional physical details are important when presenting this information in a forensic case scenario, as these details enhance the discriminatory capacity of the features, but were less important with regards to quantification of these features.

Intra-observer

The intra-observer study presents results that set out to establish the repeatability of the described technique by one observer (the author).

The presence of areas of isolated pigmentation was repeatedly identified, with an 87% agreement rate. This result does not indicate whether the same features were being identified, which was assessed by MacDonald-McMillan (2011), who found that ephelides varied significantly during an intra-observer study, thus disagreeing with the results in the current study. It is not known whether this disagreement between ephelides location was related to misidentification of the pigmentation type, which in this study would not have occurred as all pigmentation was considered together as one feature type, or whether the features were overlooked in some cases where it was identified in others.

Scars were shown to be the least repeatedly recorded feature, however this difference was shown to be insignificant, both overall and when each repeat was assessed against all others. The cause for minor disagreement in identifying scars is unknown, however it is suggested that this may be due to the ambiguity of scars with regards to their transient nature; i.e. a recent cut to healed but visible scar.

Hair was shown to be repeatedly identified. Hair is a universal trait, but the extent of coverage varies between individuals. For the purposes of this study, hair was recorded to assess its effect on the visibility of other features, rather than as a discriminate feature in its own right. Future studies would benefit from a more detailed collection of hair information, perhaps by indicating the density of the coverage.

Overall pigmentation was found to be the most repeatedly identified feature, followed by hair, and finally scars were less repeatable although were not shown to be statistically significantly different across the repeats.

Due to the fact that surface feature data was collected to supplement the vein pattern data, and was not the main focus of the thesis, this study did not consider the influence of other factors such as age, weight, body fact percentage or body side of the individuals within the images for the observer studies, so it is possible that these factors may explain some of the minor variation between repeats.

Despite this the results show that the observer was relatively consistent with identification of the three groups of features, which is important to qualify subsequent analysis of this data and provides support for this approach being used as a forensic technique.

Inter-observer

The inter-observer study presents results to establish whether the same results could be achieved by more than one individual and to assess whether observer experience influences the ability to identify surface features.

Observers B and C were the furthest apart in their level of expertise and knowledge in that observer B had no experience in any of the categories (anatomy, hand feature analysis or forensic experience) whereas observer C had extensive experience in all areas. Despite this, these two observers followed a trend. As described earlier, it cannot be known if the same feature was identified in each case due to the method of data collection, but this result does provide some evidence to suggest that identification of anatomical features from a digital image is not dependent on the level of knowledge or experience of the observer.

The remaining observers A and D were most likely to agree. These observers both had experience and knowledge of anatomy and neither had forensic experience. They differed in that observer A had no experience in hand image analysis whereas observer D had extensive experience in this area.

As with the intra-observer study, pigmentation was found to be the most repeatable feature overall. Observers B and C agreed on the presence of pigmentation, observers A and D disagreed with B and C, as well as with each other, although the differences were not statistically significant (Table 7-6).

As with the intra-observer study, scars were less repeatable than pigmentation across observers, showing a fluctuation in the responses between observers; however the differences were not statistically significant. All observers disagreed on the presence of scars; however B and C had only one difference in their report. This may be attributed to the fact that scars can be similar in colour to skin tone and so some observers may have overlooked some scars when present. Little indication as to what constitutes a scar was provided to the observers, so perhaps some observers identified a recent cut as a scar, whereas others disregarded this. Had there been further information regarding which areas the observer should consider to be a scar, this discrepancy may have been resolved. Despite these postulations, the differences were found to be statistically insignificant.

Again for hair, observers A and D reported the same number of images with hair present, whereas observers B and C disagreed both with each other and with A and D; the differences were not statistically significant (Table 7-6). The variation in identifying hair may be attributable to each observer applying their own subjective opinion i.e. hair is present but not thick enough to present an obstruction to other features. More direction from observer instructions may have reduced this subjectivity.

Further studies could expand this study by using a larger pool of observers with a greater range of experiences.

Observer studies collective discussion

In both the inter and intra-observer studies, pigmentation was shown to be the most repeatable, suggesting that the ability to identify the presence of pigmentation is robust between observers. Scars were shown to be the least repeatable feature with low levels of reproducibility, both from one observer on several occasions and by more than one observer. This suggests that scars are the most difficult feature to consistently identify. However, this does not indicate that scars should be used with caution, as the differences were insignificant. Additionally, in a forensic scenario, the anatomical or physiological definition is of less importance, instead, the importance is concerned with whether features of matching physical descriptions are found in the suspect and offender images. Overall the identification of all feature groups was shown to be repeatable, with no statistically significant differences found between repeats or observers. The results from this study support the stability of the methods to identify surface features utilised in this study, and indicates that observer experience does not influence the ability to identify features at this level of detail.

A similar result was found by Pearson (2014) who showed that both trained and untrained observers could correctly identify a hand from a pool of potential matches; however the two groups differed on the features on which they relied. In terms of relaying this information to the courts, presenting evidence that has been shown to utilise a repeatable method by a lay person will perhaps enhance the understanding of the approach to the lay person in the jury.

The method of data collection in this study was comparatively simple (Macdonald-McMillan, 2011), as this met the requirements for this research. However, it is suggested, that with a more detailed collection of information, the results may differ from those found in this study. Future studies may wish to collect the information following exact methods of a forensic investigation, by detailing physical appearance, size and relative location.

7.3 Anatomical surface features study: main results.

This section presents the results from the assessment of the anatomical surface features on the dorsum of the hand and their role in establishing similarities and differences between two individuals.

The main study had three aims; the results pertaining to each aim comprise a subsection of this chapter.

1) To determine to what extent the surface features vary in the sample population
2) To investigate the influence of biological characteristics on the ability to observe surface features;

3) To investigate how robust the surface features are when assessed in an image of poor quality (representative of a forensic case image), compared to a standardised image (representative of a suspect image taken in custody).

7.3.1 Materials and methods

All images used in this study were extracted from the VPP database. Right and left hands of 53 individuals were photographed in both the clenched fist and the semi-pronated position, and each hand pose at three levels of image quality (n = 636) (section 5.3, Table 5-5). A selection of images from this database were used to address the different aims; details of image selection will be specified in the relevant sections.

Data were extracted from the images following the materials and methods outlined in section 0 (full raw data in appendix N).

7.3.2 Results

AIM 1: Determine to what extent the surface features vary in the sample population

To generate descriptive statistics, data from the 9 mp, clenched fist images (highest quality parameters) were used to exclude variation due to image quality and hand position from the non-standardised images. R was used to generate frequency values for each of the three feature groups: pigmentation, scars and hair (Table 7-7)

Table 7-7 The distribution of surface features (9 mp, C image data)

	% Absent	**% Present**
Pigmentation	27.4	72.6
Scars	56.6	43.4
Hair	24.5	75.5

Figure 7.7 shows the frequency of pigmentation, scars and hair in the 9 mp, clenched fist dataset. It can be seen that hair (75.5%) and pigmentation (72.6%) were the most prevalent features among the population, and scars (43.4%) the least so.

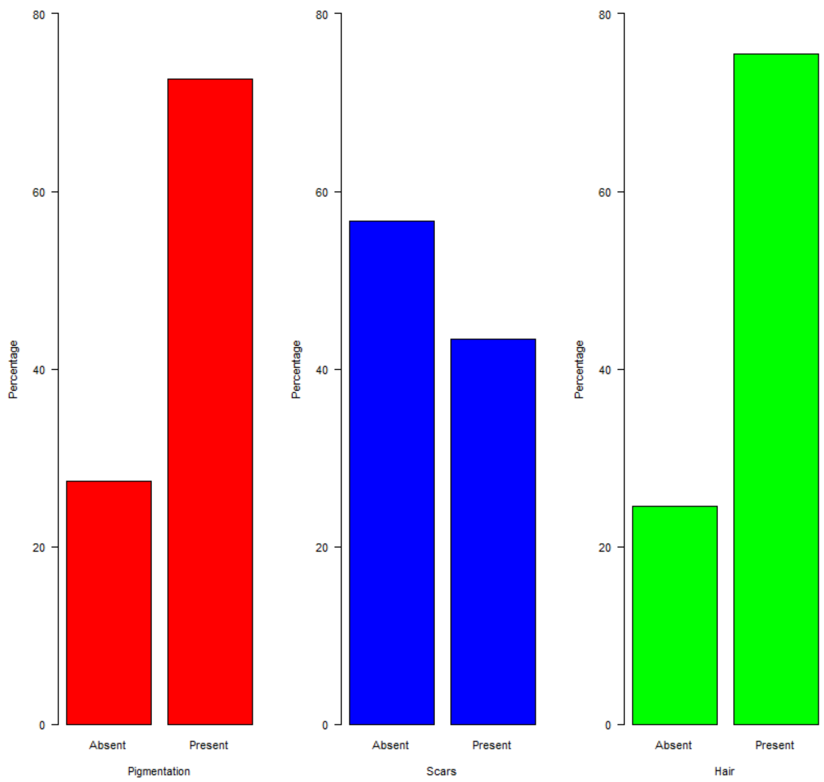


Figure 7.7 Frequency of pigmentation, scars and hair in the high quality images.

AIM 2: Influence of biological characteristics on the ability to observe surface features

Each biological characteristic (age, weight, body fat percentage and body side) was assessed to establish whether these may affect the presence of surface features. This analysis was carried out on the 9 mp, clenched fist data to minimise error from non-standardised images (n = 106).

ANOVA testing on continuous variables: age, weight, body fat %

One-way ANOVAs were conducted to determine whether the anatomical surface features (pigmentation, scars and hair) were affected by the biological characteristics.

Effect of age

The age range of the sample population was 18 to 39 years, with both the mean age (22.8 years) and mode (18 years) in the lower end of the range.

Normality was tested by the production of a Q-Q plot, which highlighted that the data was not normally distributed (Figure 7.8).

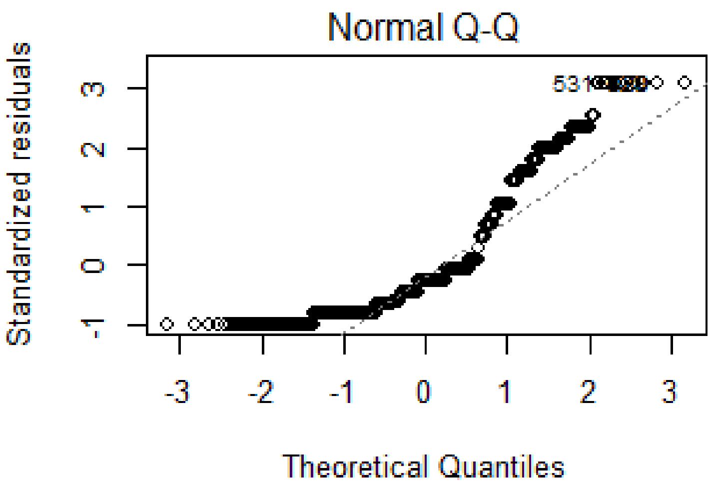


Figure 7.8 Q - Q plot for pigmentation and age, showing a departure from normality.

Due to the skew in the age data resulting in a failure of normality, the data was transformed using log function in R, before completing the ANOVA. The log transformation improved the distribution but did not normalise it entirely (Figure 7.9).

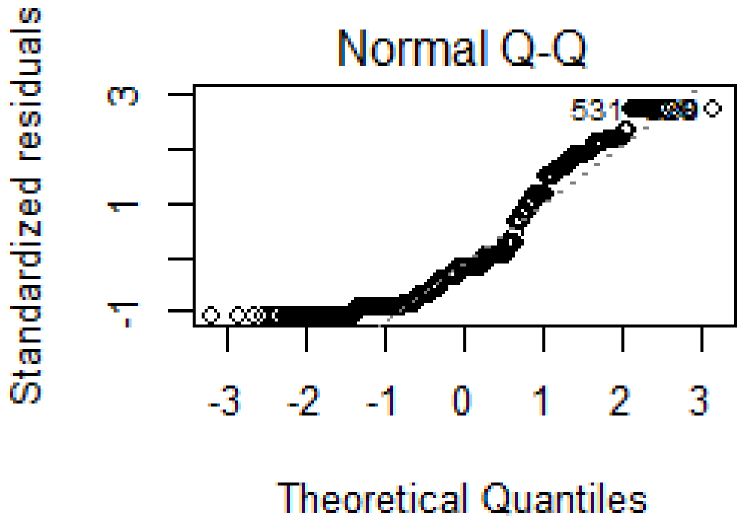


Figure 7.9 Q - Q plot for pigmentation and age after log transformation.

Pigmentation was more prevalent at the lower end of the age range, with the majority of individuals possessing visible pigmentation aged between 18 and 23 years. The majority of individuals possessing no visible pigmentation were spread across a larger range, between 18 to 31 years (Figure 7.10).The skewed distribution of individuals at the lower end of the range may contribute to the concentration of those with pigmentation grouped in this age range.

When considering the ANOVA results, it can be seen that age had some effect on the presence of pigmentation (F = 1.661), but the effect was not significant (p = 0.2) (Table 7-8).

The majority of individuals with visible scars were aged between 18 and 26 years, whilst the majority of individuals with no visible scars were aged between 18 and 24 years, suggesting that the age of the individual does not affect the presence of visible scars (Figure 7.10).

This is reiterated in the ANOVA results where it can be seen that the presence of scars was not significantly affected by age (F = 0.461, p = 0.499) (Table 7-8).

The presence of hair had the largest overall spread across the age range, with the majority of the sample with hair aged between 19 and 27 years. The majority of individuals possessing no visible hair were in the younger age group, 18 to 22 years (Figure 7.10). The ANOVA results show that the presence of visible hair was significantly affected by the age of the individual (F = 4.986, p = 0.028) (Table 7-8).

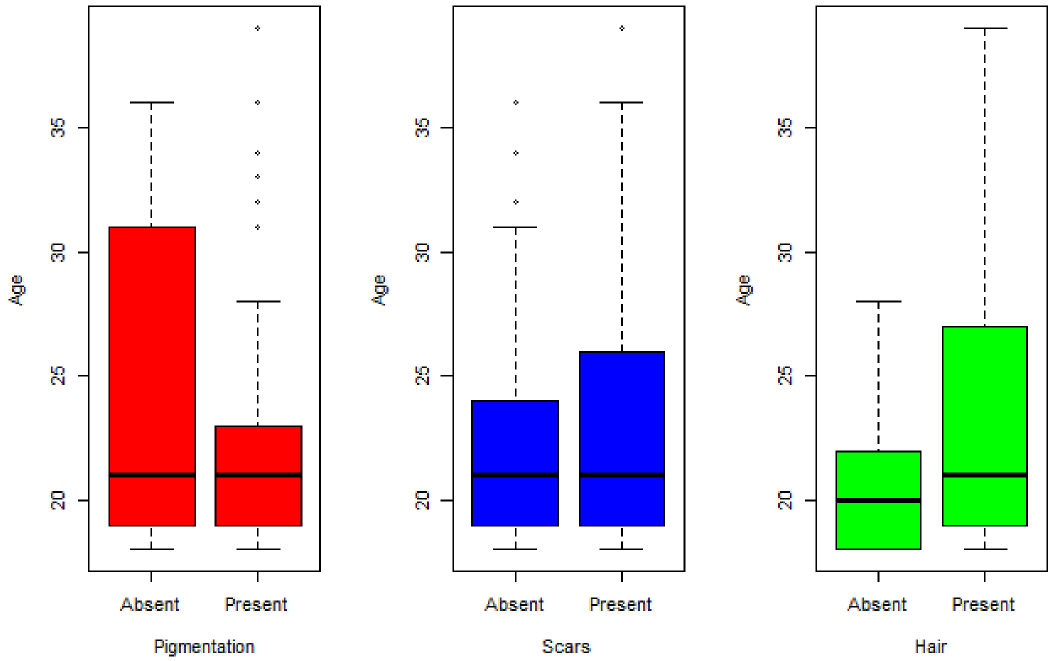


Figure 7.10 The presence of pigmentation, scars, and hair across the age range

Table 7-8 ANOVA output from tests regarding effect of age on each feature. *statistically significant p value.

Feature	Degrees of freedom	Sum of squares	Mean square	F value	P value
Pigmentation (log)	1	0.076	0.076	1.661	0.2
Residuals	104	4.731	0.045		
Scars (log)	1	0.021	0.021	0.461	0.499
Residuals	104	4.785	0.046		
Hair (log)	1	0.220	0.219	4.986	0.028*
Residuals	104	4.587	0.441		

Effect of weight

The effect of weight was examined for its effect on the ability to visualise the surface features, however no statistically significant differences were found between the presence or absence of the features (pigmentation, scars and hair) and body weight (Table 7-9).

Table 7-9 ANOVA output from tests regarding the effect of weight on each feature.

Feature	Degrees of freedom	Sum of squares	Mean square	F value	P value
Pigmentation	1	29	8.6	0.174	0.677
Residuals	104	17070	164.1		
Scars	1	30	29.71	0.181	0.671
Residuals	104	17069	164.12		
Hair	1	262	262.4	1.621	0.206
Residuals	104	16836	161.9		

Effect of body fat percentage

The effect of body fat percentage on the ability to identify surface features was examined, but no statistically significant differences were found between the presence or absence of the features (pigmentation, scars and hair), and therefore, the effect of body fat percentage was not considered any further.

Table 7-10 ANOVA output from tests regarding the effect of body fat percentage on each feature.

Feature	**Degrees of freedom**	**Sum of squares**	**Mean square**	**F value**	**P value**
Pigmentation	1	91.6	91.63	3.118	0.080
Residuals	104	3056.7	29.39		
Scars	1	21.1	21.1	0.702	0.404
Residuals	104	3127.3	30.07		
Hair	1	49.8	49.76	1.67	0.199
Residuals	104	3098.6	29.79		

Chi squared testing on categorical data

Body side

There was no significant association between the presence of pigmentation and body side (χ^2 without Yates correction = 0.05, critical value = 3.84, p = 0.83), the presence of scars and body side (χ^2 without Yates correction = 0.15, critical value = 3.84, p = 0.7) or between the presence of hair and body side (χ^2 without Yates correction = 0.12, critical value = 3.84, p = 0.91) (Table 7-11).

There were minor changes in the values from the Pearson's Chi^2 tests with and without Yates correction when considering the effect of body side, but these changes were not sufficient to alter the overall outcome of the test (Table 7-11).

Table 7-11 Observed frequencies of pigmentation, scars and hair for the left and right hands and the associated Chi^2 output.

		Pigmentation		**Scars**		**Hair**	
		Absent	**Present**	**Absent**	**Present**	**Absent**	**Present**
Side	**Left**	15	38	29	24	12	39
	Right	14	39	31	22	12	41
Degrees of freedom		1		1		1	
χ^2 with Yates correction		0		0.038		0	
Critical value		3.84		3.84		3.84	
P value		1		0.845		1	
χ^2 without Yates correction		0.05		0.15		0.12	
Critical value		3.84		3.84		3.84	
P value		0.83		0.7		0.91	

Body hair and obscured region of interest

The conditional probabilities of identifying pigmentation or scars, when hair was also identified show that the probability of identifying pigmentation in the presence of hair (0.68) is higher than locating scars in the presence of hair (0.39), suggesting that the presence of hair affects the ability to identify scar more so than pigmentation. However, when looking at the probability for both pigmentation and scars alone, compared to in the presence of hair, the effect of hair was comparable for both features.

Table 7-12 Matrix showing the conditional probabilities of identifying surface features.

	Pigmentation	**Scars**	**Hair**
Pigmentation	P(Pigm) = **0.72**	P(Pigm | Scars) = **0.72**	P(Pigm | Hair) = **0.68**
Scars	P(Scars | Pigm) = **0.43**	P(Scars) = **0.43**	P(Scars | Hair) = **0.39**
Hair	P(Hair | Pigm) = **0.70**	P(Hair | Scars) =**0.67**	P(Hair) = **0.75**

AIM 3: The effect of case specific conditions on surface feature distribution.

This section addresses the effect of image quality and hand position on the presence or absence of the anatomical surface features. This section will introduce data from the full dataset, to assess all variables (Table 5-5).

To ensure all variables were considered independently, the two hand positions and the effect of image quality were assessed separately. The final section then compares image quality results across the two hand positions.

The effects of image quality in the clenched fist position

Data from the clenched fist position was explored to assess whether the different levels of image quality (high, medium and low) influence the level of detail extracted from digital images.

Pigmentation

Pigmentation was most prevalent in the high setting (present in 72.6% of the sample), followed by the low setting (47.2%) and finally least prevalent in the medium setting (46.2% present) (Figure 7.11).

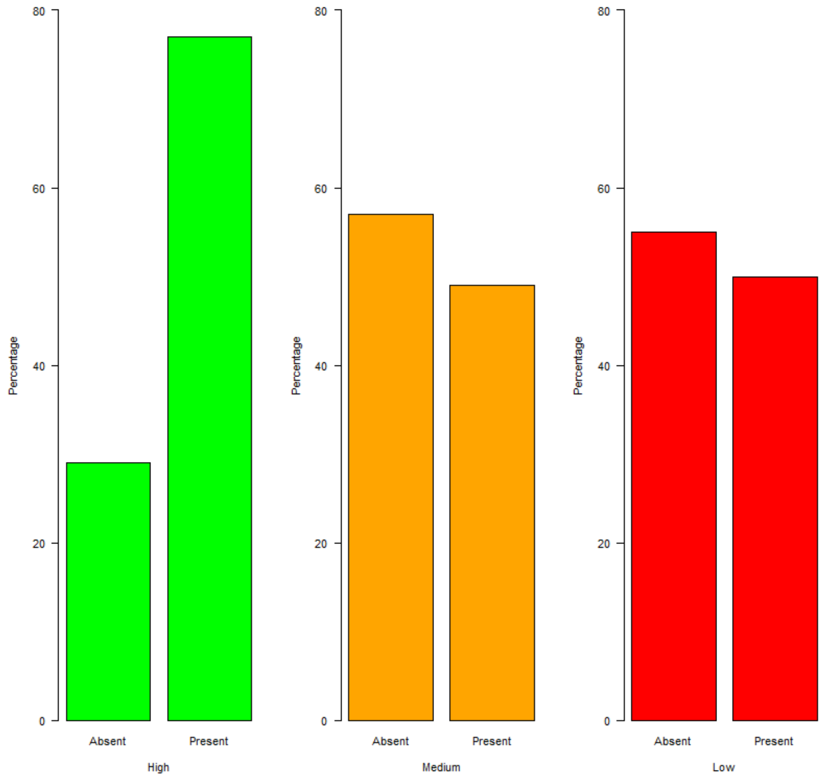


Figure 7.11 The presence or absence of pigmentation across the three image settings (high: green, medium: orange, low: red) (C image data)

Results from the Pearson's Chi^2 test show that the differences in the recorded presence of pigmentation were significantly different between the high and medium settings ($p = 0.015$), and between the high and low settings ($p = 0.020$) (Table 7-13). This validates rejecting the null hypothesis, and supports the hypothesis that image quality significantly affects the level of detail observed from images, but only when comparing the highest setting with the lower two settings. The differences when comparing the recorded presence between the low and medium settings were not significantly different. ($p = 0.918$) (Table 7-13).

Table 7-13 Table showing the p values from the Chi^2 tests regarding the presence of pigmentation at varying levels of image quality. * = where Chi^2 value exceeded the critical value.

	High	Medium	Low
High	0	0.015*	0.020*
Medium		0	0.918
Low			0

Scars

As the image quality decreased, the number of scars observed also decreased. Scars were most prevalent in the highest quality images (43.4%), less in the medium quality images (37.7%) and less still in the lowest quality images (20.8%) (Figure 7.12).

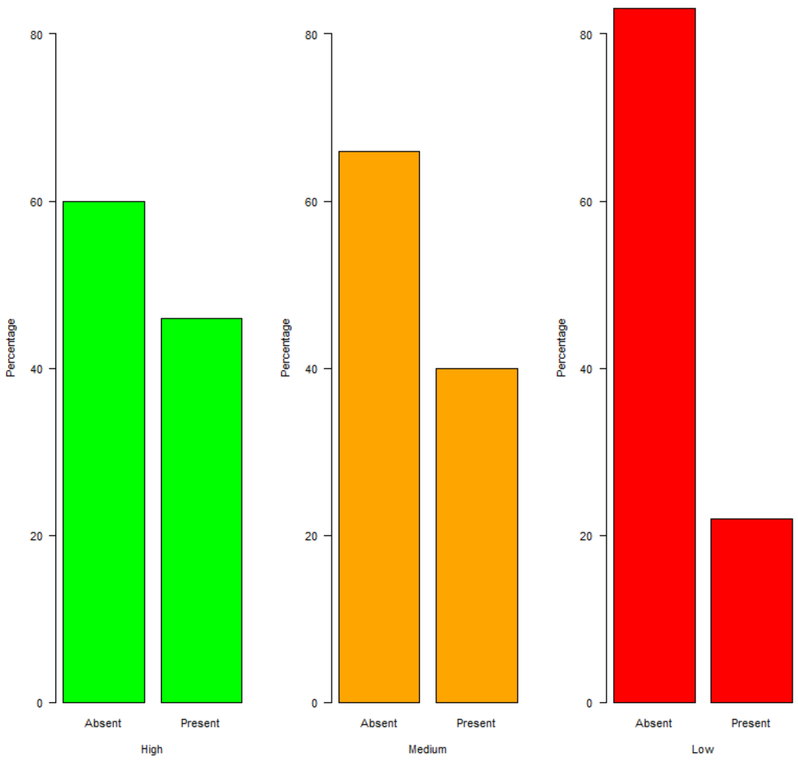


Figure 7.12 The presence of scars across the three image setting (high - green, medium - orange, low - red) in the clenched hand position (C image data)

The results from the Pearson's Chi^2 test show that the differences in recorded presence of scars was significantly different between the high and low settings (p = 0.005) and between the medium and low settings (p = 0.021). In both these cases the value of Chi^2 exceeded the critical value, therefore validated rejecting the null hypothesis. However, when considering the differences in recorded presence of scars between the high and medium settings, the differences were found to be insignificant (p = 0.527) (Table 7-14)

Table 7-14 Table showing the p values from the Chi^2 tests regarding the presence of scars at varying levels of image quality. * = where Chi2 value exceeded the critical value.

	High	**Medium**	**Low**
High	0	0.527	0.005*
Medium		0	0.021*
Low			0

Hair

The number of images recorded as having hair present decreased as the image quality decreased, indicating that image quality affects the amount of information available. Hair was most prevalent in the highest quality images (75.5%), less in the medium quality images (74.5%) and less still in the lowest quality images (55.7%) (Figure 7.13).

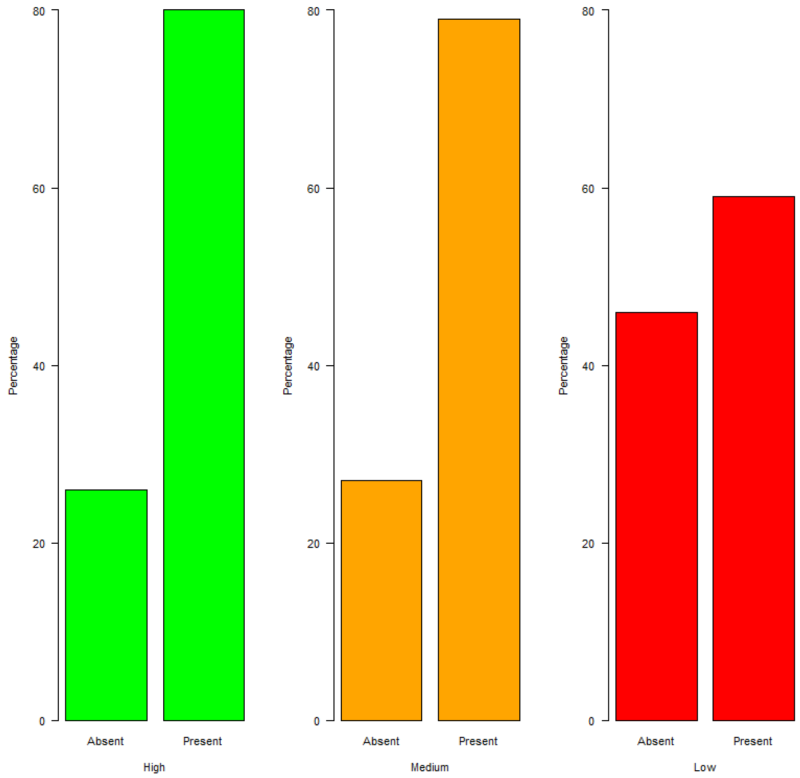


Figure 7.13 The presence of hair across the three image setting (high: green, medium: orange, low: red) (C image data)

It was seen from the results of Chi^2 tests, that there were no statistically significant differences observed between any of the three levels of image quality (Table 7-15).

Table 7-15 Table showing the p values from the Chi^2 tests regarding the presence of hair at varying levels of image quality.

	High	**Medium**	**Low**
High	0	0.935	0.084
Medium		0	0.090
Low			0

The effect of image quality in the semi-pronated hand position

Data from the semi-pronated hand position was explored to assess whether the different levels of image quality (high, medium and low) influence the level of detail extracted from the images in this position. In the semi-pronated position, areas of the hand are observed that are not visible in the clenched fist position (the lateral aspect/surface of the thumb region), whereas other areas are obscured, namely the medial aspect of the hand.

Pigmentation

The number of images where pigmentation was recorded as present decreased as the image quality decreased; most prevalent in the highest quality images (74.5%), less in the medium quality images (58.5%) and less still in the lowest quality images (57.5%) (Figure 7.14).

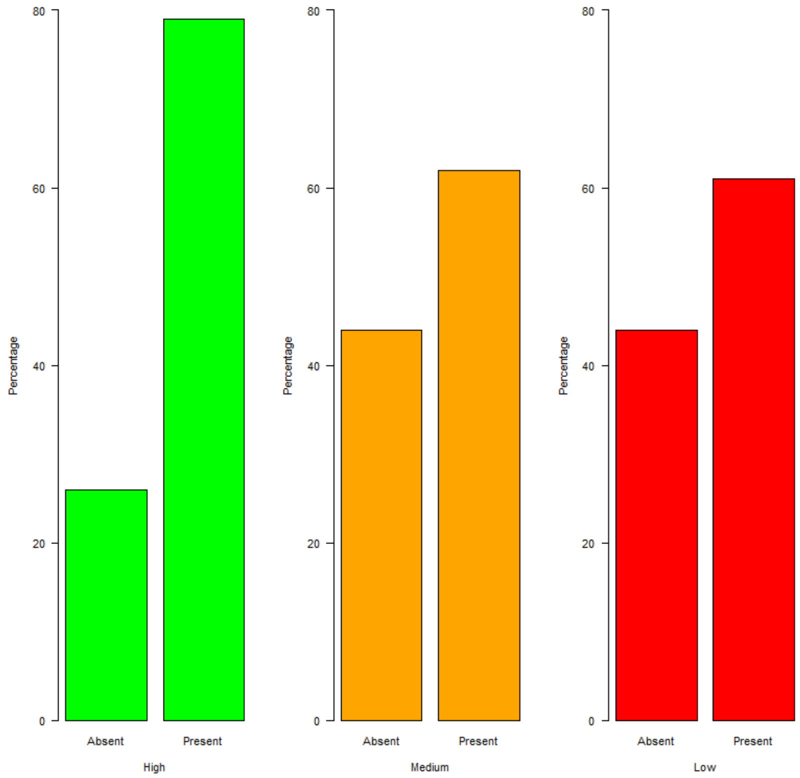


Figure 7.14 The presence of pigmentation across the three image settings (high: green; medium: orange; red: low) (Sp image data).

The results from the Pearson's Chi^2 test show that the differences in the presence of pigmentation was not significantly different between any of the three image settings (Table 7-16).

Table 7-16 Table showing the p values from the Chi^2 tests regarding the presence of pigmentation at varying levels of image quality.

	High	**Medium**	**Low**
High	0	0.165	0.139
Medium		0	0.926
Low			0

Scars

Scars were most readily identified in the high setting (44.3%), followed by the medium setting (36.8%) and finally least in the low setting (26.4% present) (Figure 7.15) again showing a decline in features observed as the image quality declined.

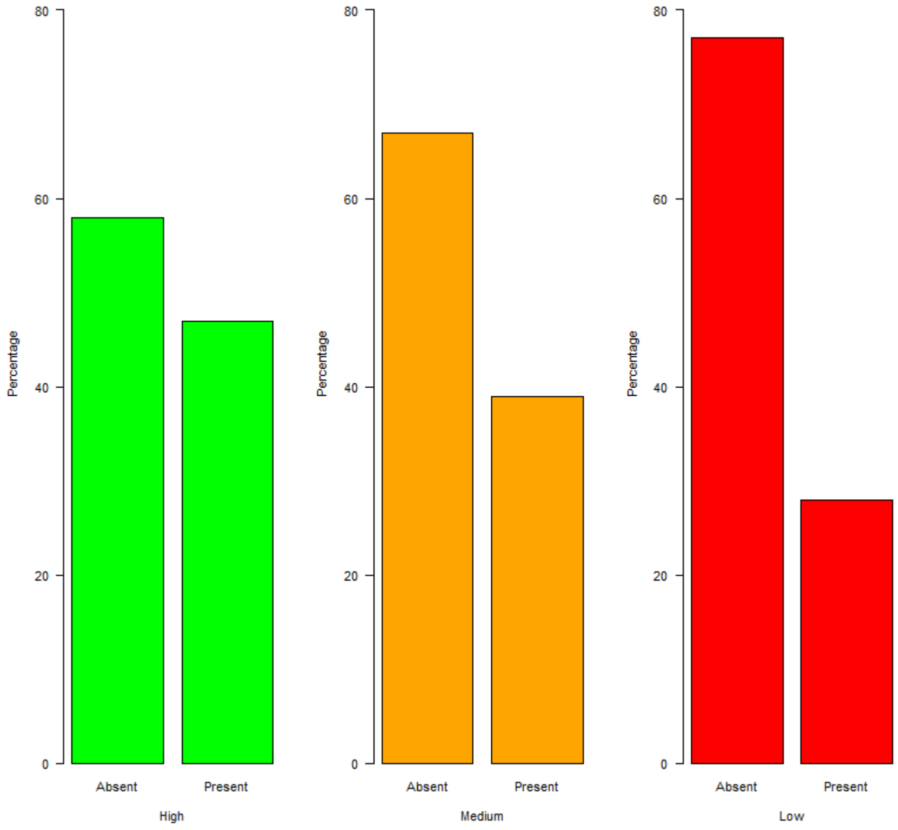


Figure 7.15 The presence of scars across the three image setting (high - green, medium - orange, low - red) (Sp image data).

Results from the Pearson's Chi^2 test show that only between the high and low settings were the differences in recorded presence of scars significantly different ($p = 0.033$) (Table 7-17).

Table 7-17 Table showing the p values from the Chi^2 tests regarding the presence of scars at varying levels of image quality. * = where Chi^2 value exceeds the critical value.

	High	**Medium**	**Low**
High	0	0.405	0.033*
Medium		0	0.191
Low			0

Hair

Hair was most prevalent in the medium setting (78.3%) followed by the high setting (77.4%), and finally least prevalent in the low setting (50.9%) (Figure 7.16)

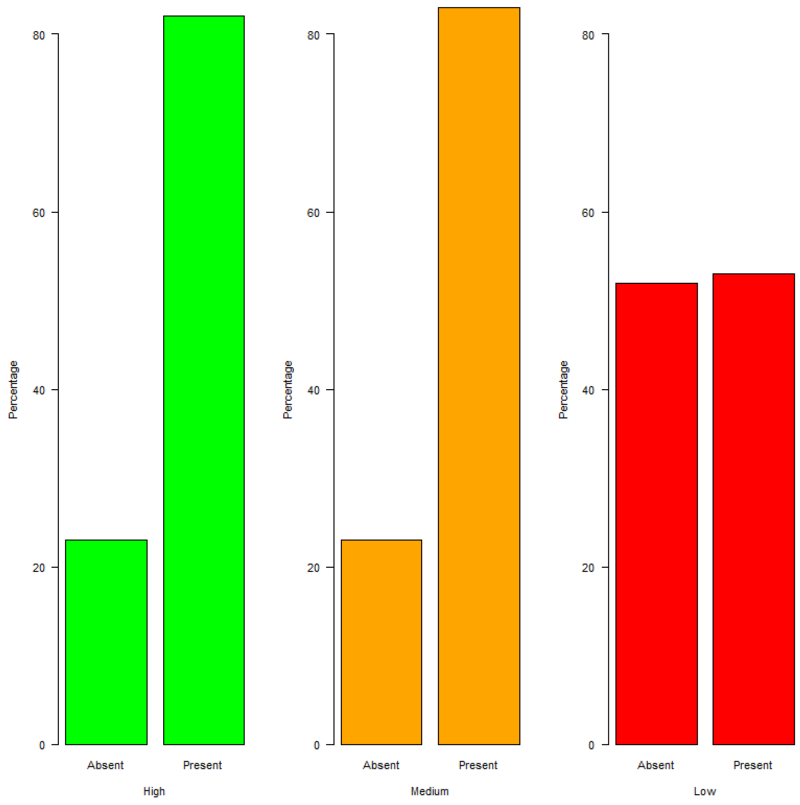


Figure 7.16 The presence of hair across the three image settings; (high: green, medium: orange, low: red) (Sp image data).

The results from the Pearson's Chi^2 test shows that the differences in the recorded presence of hair in the Sp position were significant when comparing results from the high and low image settings ($p = 0.019$), and between the medium and low settings ($p = 0.016$) (Table 7-18).

Table 7-18 Table showing the p values from the Chi^2 tests regarding the presence of hair at varying levels of image quality. * = where Chi^2 value exceeds the critical value.

	High	**Medium**	**Low**
High	0	0.943	0.019*
Medium		0	0.016*
Low			0

The effects of hand position at all levels of image quality

Data from the clenched fist and semi-pronated hand position was then combined to assess the effect of hand position at each level of image quality.

Pigmentation

Figure 7.17 shows that pigmentation was recorded as present more in the semi-pronated hand position than compared to the clenched fist position at all levels of image quality, suggesting pigmentation is more likely to be present on the region of the hand seen in the semi-pronated position, irrespective of image resolution.

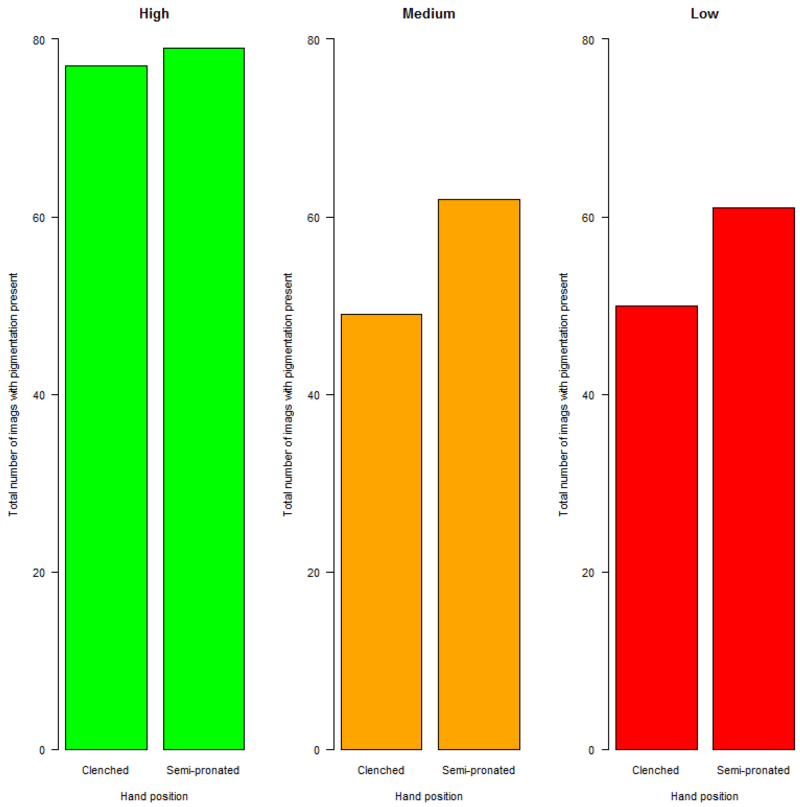


Figure 7.17 Percentage of images with pigmentation from the clenched fist and the semi-pronated position, present at high, medium and low quality images.

However, when considering the results from Pearson's Chi^2 tests, it can be seen that areas of isolated pigmentation were not significantly influenced by the position of the hand, in all three levels of image quality (Table 7-19).

Table 7-19 Chi^2 output for pigmentation across both hand positions, for all levels of image quality.

Image quality	**Degrees of freedom**	**Critical value**	χ^2	**P value**
High	1	3.84	0.025	0.876
Medium	1	3.84	1.445	0.230
Low	1	3.84	1.013	0.314

Scars

Figure 7.18 shows that scars were recorded as present more in the semi-pronated hand position than compared to the clenched fist position in the high and low image quality levels. However, more scars were observed in the clenched fist compared to the semi-pronated position in the medium quality images.

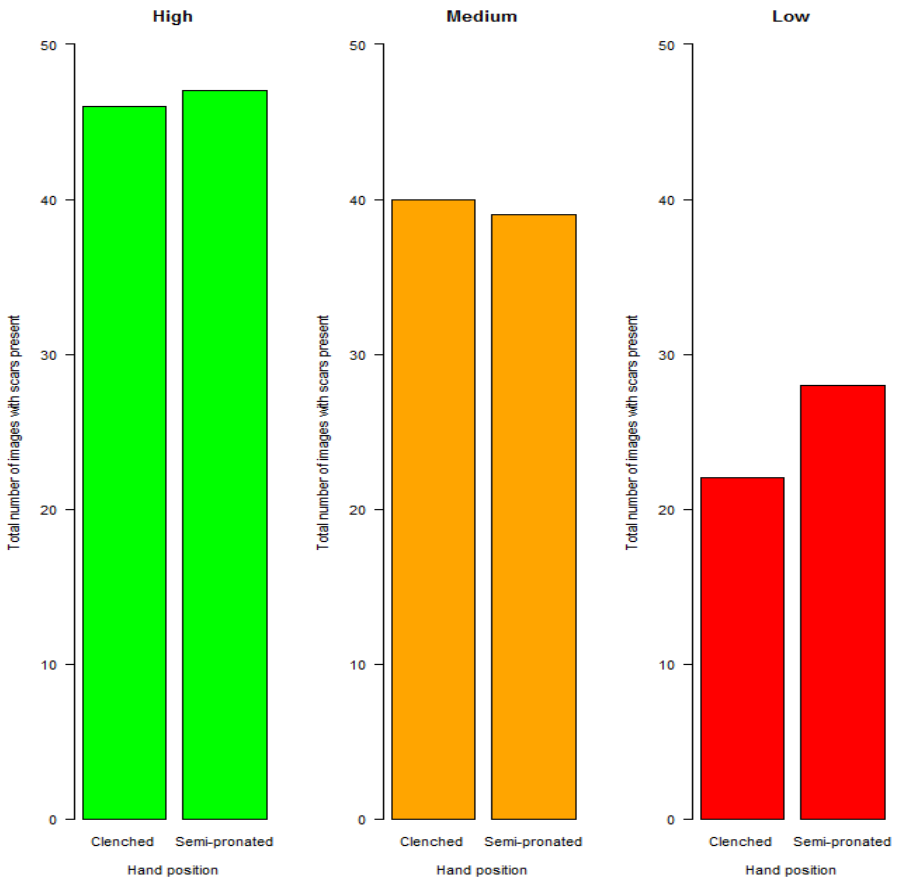


Figure 7.18 Percentage of images with scars from the clenched fist and the semi-pronated position, present at high, medium and low quality images.

The results from the Pearson's Chi^2 tests show that scars were not significantly influenced by the position of the hand, in all three levels of image quality (Table 7-20).

Table 7-20 Chi^2 output for scars across both hand positions, for all levels of image quality.

Image quality	Degrees of freedom	Critical value	χ^2	P value
High	1	3.84	0.009	0.923
Medium	1	3.84	0.011	0.917
Low	1	3.84	0.664	0.415

Hair

Figure 7.19 shows that hair was more frequently recorded in the semi-pronated hand position than compared to the clenched fist position in the high and medium image quality levels; however, hair was more often observed in the clenched fist compared to the semi-pronated position in the low quality images. Despite these observations, Chi^2 testing showed that hair was found to be insignificantly influenced by the position of the hand, in all three levels of image quality (Table 7-21).

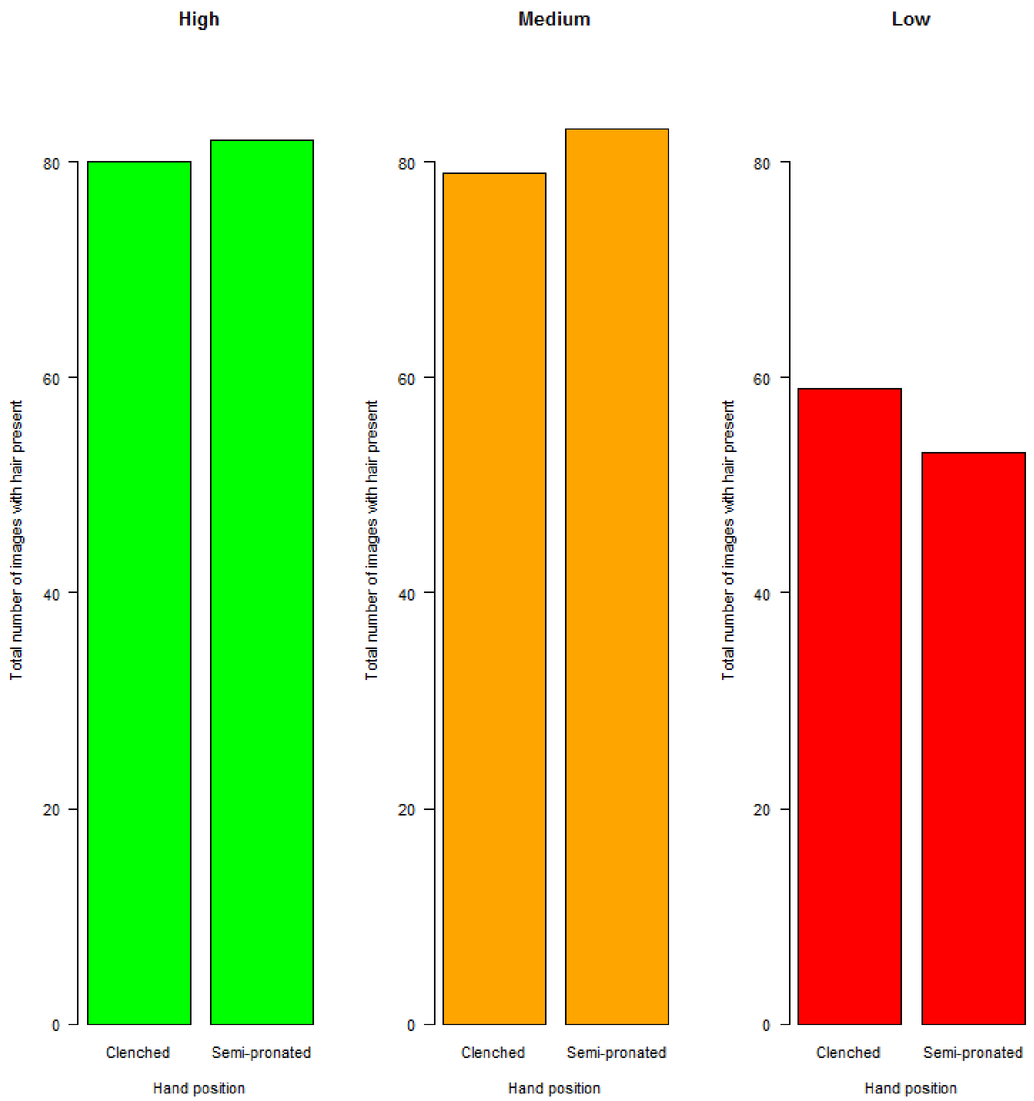


Figure 7.19 Percentage of images with hair from the clenched fist and the semi-pronated position, present at high, medium and low quality images.

Table 7-21 Chi^2 output for hair across both hand positions, for all levels of image quality.

Image quality	**Degrees of freedom**	**Critical value**	χ^2	**P value**
High	1	3.84	0.024	0.878
Medium	1	3.84	0.095	0.759
Low	1	3.84	0.216	0.642

7.3.3 Surface feature study discussion of results

The main section of results regarding the surface features establishes the distribution of features in the sample population in the first instance. Secondly, to consider whether biological characteristics of the individual may affect the presence of features, and finally to establish if images akin to forensic case images (images of lower quality and without standardisation) affect the visibility of these structure.

For the purposes of this study ephelides, melanocytic nevi and lentigines were collated and classified as 'areas of isolated skin pigmentation'. This was deemed appropriate due to the difficulty in distinguishing between these features because of the similarity in visual appearance (section 4.1.4). Additionally, previous research recommended that these features be grouped in this way (Macdonald-McMillan, 2011). Furthermore, it was thought that the presence of a pigmented area on the skin may be discriminatory, irrespective of its anatomical or clinical classification.

AIM 1: Determine to what extent the surface features vary in the sample population

To consider the prevalence and distribution of surface features irrespective of other factors that may influence variation, only images from the 9 mp, clenched fist (highest quality parameters) dataset were analysed in this section.

Pigmentation

Isolated areas of hyper-pigmentation were the second most prevalent surface feature, found in 72.6% of the sample (Table 7-7, Figure 7.7). A similar value was observed by Bastiens *et al.* (1999) who found that 73.9% of individuals had solar lentigines and 47.8% had ephelides present. The prevalence of ephelides has also been found to vary from 8.38% (Yang *et al.*, 2007) to 24.8% (Pavlotsky *et al.*, 1997), whereas melanocytic nevi (MN) presence was reported as being as low as 11.8% (Pavlotsky *et al.*, 1997). It is difficult to compare directly the current study values with other relevant studies in the literature, as the way in which pigmentation has been reported differs.

Additionally, the demographic selected for this study comprised Caucasian males, which may affect the level of pigmentation present in comparison to some studies that used Israeli males (Pavlotsky *et al.*, 1997) and Taiwanese children aged 6 – 11 years (Yang *et al.*, 2007).

This high prevalence of isolated areas of hyper-pigmentation reported in the current study suggests that the presence of pigmentation may not be a discriminatory feature. However, in current forensic examination methods, the relative location and physical appearance would also be considered; therefore potentially increasing the discriminatory capacity of pigmentation as a feature. For example, it may be possible for an individual to possess the same number of areas of pigmentation, but the precise visual appearance and location could provide enough differences between the two sets of images to be discriminatory.

Areas of isolated pigmentation were the third most commonly used feature type in case work conducted in CAHId (used in 43.5%), therefore awareness of the expected prevalence of pigmentation will benefit experts in their reporting of this type of evidence.

Scarring

Scars were the least common feature observed (43.4%). (Black *et al.*, 2013a) found that scars were present in 51% and 60% in male right and left hands respectively, 32.05% of which were found on the dorsal surface of the hand, excluding the fingers.

Despite having the lowest incidence of all of the surface features, the prevalence of scars identified is still relatively high to be considered as a discriminatory feature, if only its presence were considered. To reiterate the argument for pigmentation, in forensic investigations scar information would be presented with a detailed description of its appearance, location and orientation; these additional details would provide for a potential discrimination between two sets of images.

Hair

Hair on the dorsal surface of the hand is a universal trait (Szabo, 1967); however it is not clearly visible in all individuals. The data from this research shows that 25% of individuals have no visible hair.

The current research does not account for the density of visible hair, which is thought to be highly variable in the 75% of the individuals where hair was observed. Future studies would benefit from assessing the density of visible hair to establish the level at which the hair begins to obscure other surface features.

AIM 2: Influence of biological characteristics on the ability to observe surface features

To consider the influence of biological characteristics on the presence of surface features, irrespective of other factors that may influence variation, only images from the 9 mp, clenched fist category were analysed in this section. This dataset holds only the highest image quality parameters, without other images that may introduce sources of error (such as positional changes and images of lower quality).

Age

The age range of the sample was 18 to 39 years, the mean being 22.8 years. The sample was skewed towards the lower end of the age range, so this should be carefully considered when interpreting results relating to age. An attempt was made to improve the normality of the data; however, transformation using the log function did not restore normality entirely.

It was found that there was no statistically significant relationship between age and the presence of pigmentation (p = 0.2) or scars (p = 0.49); however there was a statistically significant relationship with hair and age (p = 0.027) (Figure 7.10, Table 7-8).

With regards to pigmentation and age, the data from this research indicates that there is no significant relationship. The age range used in this study is relatively narrow (21 years), therefore had a larger range of ages been considered, perhaps there may have been an indication of an effect on the presence pigmentation from age. Other studies have shown that different types of pigmentation behave in different ways with regards to aging; the prevalence of MN have been reported to peak at around 15 years, before gradually fading with increasing age (Stegmaier, 1959). Had the age range been extended in the current study, individuals may have possessed pigmentation at various stages of the life cycle of the nevus, and therefore a clearer indication of the distribution with age may have been apparent.

The situation is further complicated by the fact that it has been reported that ephelides decrease with age, whilst lentigines have been reported to increases with age (Bastiaens *et al.*, 2004, 1999; Monestier *et al.*, 2006). To assess the effect of age properly, the individual groups of pigmentation would have to be assessed as they behave differently in relation to age. Despite this, the data acquired are sufficient for the purposes of this study.

With regards to scars, other research has reported the highest prevalence of hand injuries to be in males aged between 12 and 29 years (Clark *et al.*, 1985); these figures relate to hand injuries only and not the presence of scars; it cannot be known if the injuries reported would have resulted in permanent scarring. The current research found the majority of individuals with scars were aged between 18 and 26 years, however, the majority of those without scars were of a similar age group, between 18 and 24 years.

Although this range seems to agree with the overall finding of Clark *et al.* (1985), it may be misleading due to the skew in the age range.

Hair was the only feature found to have a statistically significant relationship with age; showing that there were more individuals aged above 22 years with hair present. The majority of individuals with no visible hair were in the lower end of the range (18 – 22 years). Despite the statistically significant results from the data, this cannot be substantiated against relevant literature, as there is a paucity of relevant research on which to rely; therefore the situation with hair and age cannot be commented on further.

In the context of this research, it was important to assess the influence of age, as when presented with an individual in a forensic case scenario, it may be useful to know if the individual has a particularly high incidence of pigmentation, scars or hair for their age or otherwise.

Weight and body fat percentage

No statistically significant relationship was found between weight or body fat percentage and the presence of surface features. Weight and body fat percentage data were collected to assess the effect these may have on the ability to visualise the superficial vein pattern, therefore the non-significant relationships found were not surprising.

Body side

In the current study it was found that body side was not significantly related to the presence of pigmentation ($p = 0.83$), scars ($p = 0.7$) or hair ($p = 0.91$) (Table 7-11).

Converse to the findings in this research, Macdonald-McMillan (2011) found that all three types of pigmentation (ephelides, melanocytic nevi and lentigines) showed significant differences between the left and right hands of male individuals; however this was only in relation to specific locations, which comprised a portion of the dorsum of the hand, and not the dorsum of the hand as a whole. This highlights that perhaps the location of the feature is more discriminative that it's presence alone. In the same study by Macdonald-McMillan (2011), it was also found that the left hands possessed significantly more scars than the right hands in male individuals, which was not found in the current study.

Body hair and obscured region of interest

The probability of identifying pigmentation (0.68) and scars (0.39) in the presence of hair was not significantly different from the probability of identifying pigmentation (0.72) and scars (0.43) irrespective of hair, suggesting that hair does not significantly hinder the visibility of other surface features (Table 7-12). However, because the presence of hair was so prevalent and the density of hair coverage was not recorded, it is difficult to draw conclusions from this data.

Further studies should consider including a scale with regards to hair coverage to explore this further; to examine how different levels of coverage affect the ability to identify surface features.

AIM 3: The effect of case specific conditions on surface feature distribution

For this section of the study, all images were utilised to assess variables that may be encountered in a forensic case image, such as; varying hand position and image quality.

The effects of image quality

Clenched fist position

Pigmentation was found to be least prevalent in the medium image setting; however, the difference between the low and medium settings equated to 1%. A significant relationship was observed for pigmentation between the high and low settings ($p = 0.020$) and the high and medium settings ($p = 0.015$) (Table 7-13).

Scars and hair were mostly identified in the high image setting, followed by the medium settings, with the low setting (mobile phone camera) showing the lowest prevalence of features. Statistically significant differences in scar observation was seen between the high and low settings ($p = 0.005$) and between the medium and low ($p = 0.021$) (Table 7-14).

With regards to hair, there were no statistically significant differences seen between any levels of image quality (Table 7-15).

The largest difference was consistently found between the highest and lowest settings (9 mp Fujifilm DSLR, and mobile phone), although in the case of hair, the difference was not significant.

This supports the hypothesis that more information is available in the ‘suspect-type’ images compared to the ‘offender-type’ images; information which forensic practitioners can rely on when presenting their evidence involving the comparison of two sets of images of varying quality/resolution.

Semi-pronated position

With regards to the semi-pronated positon images, there were no statistically significant differences seen between any levels of image quality with regards to pigmentation observation (Table 7-16).

For scars, a significant difference was observed only between the high and low setting ($p = 0.033$) (Table 7-17), whereas for hair in the Sp position, significant differences were seen between the high and low ($p = 0.019$) and the medium and low settings ($p = 0.016$) (Table 7-18).

In the semi-pronated position pigmentation and scars were identified most readily in the high, then medium settings, with the low setting (mobile phone camera) showing the least incidences of features present. Hair differed slightly in that the highest incidence was identified in the medium image setting, followed by the high setting, with the low setting showing the least features present.

The difference in position has already been reported, but it is interesting to note that image quality appears to affect feature visibly differently in the clenched position, than in the semi-pronated position, although this may be due to the differences in position of the hand rather than the image quality.

Overall image quality has shown to have a significant effect on the features observed from within a digital image. This should be borne in mind when assessing forensic images and making comparisons to police captured suspect images, as the results from this study have shown that information is lost when image quality is reduced.

In most cases, difference were significant between the high (09 mp, Fujifilm DSLR) and low (mobile phone images). With a high incidence of forensic case images presenting on mobile phone devices, and the custody suite predominantly using a higher quality DSLR camera, the results from this study will play a valuable role in reporting expected information loss between suspect and offender images.

The effects of hand position

All surface features were recorded at a higher prevalence in the semi-pronated position, compared to the clenched position (with the exceptions of scars in the medium quality images and hair in the low quality images); however none of the differences were significant (Table 7-19, Table 7-20, Table 7-21).

The medial aspect of the dorsum of the hand was obscured in the semi-pronated position, whereas the lateral aspect was more exposed. Black *et al.* (2013b) reported that melanocytic nevi were most likely to be found laterally and centrally on the dorsum of the hand (Figure 3.6), both locations which are visible in the semi-pronated position. Therefore the findings in this study, although not significant, are comparable with the findings of Black *et al.* (2013).

With regards to scar location, Black *et al.* (2013a) found that the majority of scars were present in the index and middle finger 'corridors' (Figure 3.7), again in the lateral to middle aspect of the dorsum of the hand. Although the findings in this research were not significant, the results are comparable to the findings of Black *et al.* (2013a)**.** Rosberg and Dahlin (2004) found that hand injuries were most common at both the lateral and medial borders of the hand. The medial border was not seen in the Sp position, and partially seen in the clenched position.

With regards to hair coverage, the current research suggests that more hair was present in the semi-pronated position, than the clenched fist; again laterally rather than centrally or medially. This disagrees with Schmidt and Lanz (2003) who found that hair tends to be thicker along the hypothenar eminence (medial), and the thumb region (lateral) is relativity free of hairs; although the hypothenar eminence was not visible in with the C or Sp position, and therefore cannot be compared directly. Setty (1964) also found that hair can be restricted to the medial border, occasionally however hair may be found over the anatomical snuffbox (Figure 3.8). The disagreement in hair location may be due to variation in collection methods; i.e. the current research extracted the data from digital images, whereas Schmidt and Lanz (2003) and Setty (1964) examined the individuals in person.

Surface features main study results: overall discussion.

The results from this study go some way to clarifying the overall prevalence of surface features on the dorsum of the hand, however as this data were recorded to be used in conjunction with vein pattern data, detailed information relating to each feature is lacking. Despite this, the investigation into the effect of changes in hand position and image quality has not been reported previously in the literature, and therefore, this study adds to the literature by providing supportive information to the level of detail lost between suspect and offender images.

This information will benefit the forensic practitioner in their reporting of the difference and similarities between suspect and offender images, and provide additional detail to the evidence being presented.

8 FEATURE COMBINATION STUDY

Chapters and 7 have demonstrated the distribution and variation of vein patterns and surface feature across the sample population. Thus far, the two feature groups have been considered independently, however in forensic investigations, it is likely that more than one type of feature will be assessed to establish similarities and differences between suspect and offender images. The majority of relevant cases performed by the team at CAHId used six different types of features (section 4.4). Additionally, there is a developing theme in biometric literature of utilising a multi-modal approach to identification, as it is argued to be more robust than using only one feature (Hong *et al.*, 1999; Jain *et al.*, 2004a; Mohammed *et al.*, 2014; The Federal Bureau of Investigation, n.d.).

To address this issue, this chapter will introduce the assessment of both feature groups (surface features and vein networks), to investigate the following aims:

1. To determine whether there is an association between the presence of vein network features and surface features, i.e. a level of co-dependence as opposed to independence
2. To ascertain the incidence of feature combinations, considering all feature groups.

8.1 Materials and methods

8.1.1 Description of the images

Data from the 9 mp, clenched fist position dataset was utilised to assess feature combinations, without introducing known sources of variation from varying hand position and image resolution.

8.1.2 Data analysis

Feature dependency analysis

ANOVA testing was used to assess the inter-dependency of features across the two main feature groups; vein networks and surface features. This reported whether there was a significant relationship between surface features being present or absent and the vein network features (in this instance number of nodes and edges).

Feature combination analysis

To assess feature combinations, a vector was created in R© (Appendix O). Data relating to pigmentation, scars, hair, nodes, edges, loops and intersections were entered into the vector. Pigmentation, scars and hair were entered as originally recorded; in a binary format, considering whether the feature was present (1) or absent (0). Loops and intersections were also considered in a binary format; present (true) or absent (false). The number of edges and nodes were continuous variables; to enable comparison, these features were grouped (sparse, intermediate and dense), to change the variable to categorical. The number of edges and nodes were grouped into three categories depending on the lower 25%, middle 50% and upper 25 quantiles of the data (Table 8-1). These divisions were chosen as they coincide with the distribution of boxplot quantiles.

Table 8-1 Table showing how the number of nodes and edges were separated into three groups.

Category	**Quantiles**	**Edges**	**Nodes**
Sparse (Low (**L**))	Lower 25%	5 to 8	6 to 9
Intermediate (Medium (**M**))	Middle 50%	9 to 16	10 to 15
Dense (High (**H**))	Upper 25%	17 to 28	16 to 24

The fully constructed vector contained 7 variables; the presence of surface features (pigmentation, scars and hair) and vein network features (nodes, edges, intersections and loops) for each individual. This vector was constructed using the 9 mp, clenched fist sub group of data (n = 106). An example of this vector is shown in Table 8-2; the full vector can be found in appendix O.

Table 8-2 Example of the full vector, detailing the presence or absence of the surface features and vein network details.

Intersections	**Loops**	**No. Edges**	**No. Nodes**	**Pigmentation**	**Scar**	**Hair**
FALSE	TRUE	H	H	0	1	1

Once this vector was constructed (each row related to one hand image), it was converted to a 'string variable' so that each row, with its combination of features, was considered as a single data point. From this, the number of times each combination of features occurred could be quantified.

There were a total of 288 possible combinations of features; calculated by the following equation; five groups with binary data (i.e. two levels; present (1) or absent (0)), and two groups with three levels (high, medium and low) (Equation 8-1).

Equation 8-1: $Total\ number\ of\ possible\ feature\ combinations = 2^5 \times 3^2 = 288.$

This full vector shall be referred to as the maximum vector. Upon assessing the features that were not present in the most common combinations, these features were removed, so that fewer features were considered in a logical manner. Calculations as to how many combinations were possible with each number of features is explained in the relevant section.

8.2 Results

8.2.1 Feature dependency

This section will determine the association or lack thereof; between the presence of vein network features and surface features. It was hypothesised that the vein networks, scars and pigmentation would not be dependent, as there is no known embryological, genetic or environmental evidence in support of such a relationship.

Number of nodes and surface features

ANOVA testing supports the hypothesis of no relationship and indicates that there were no statistically significant interactions between the number of nodes present and pigmentation scars or hair (Figure 8.1, Table 8-3).

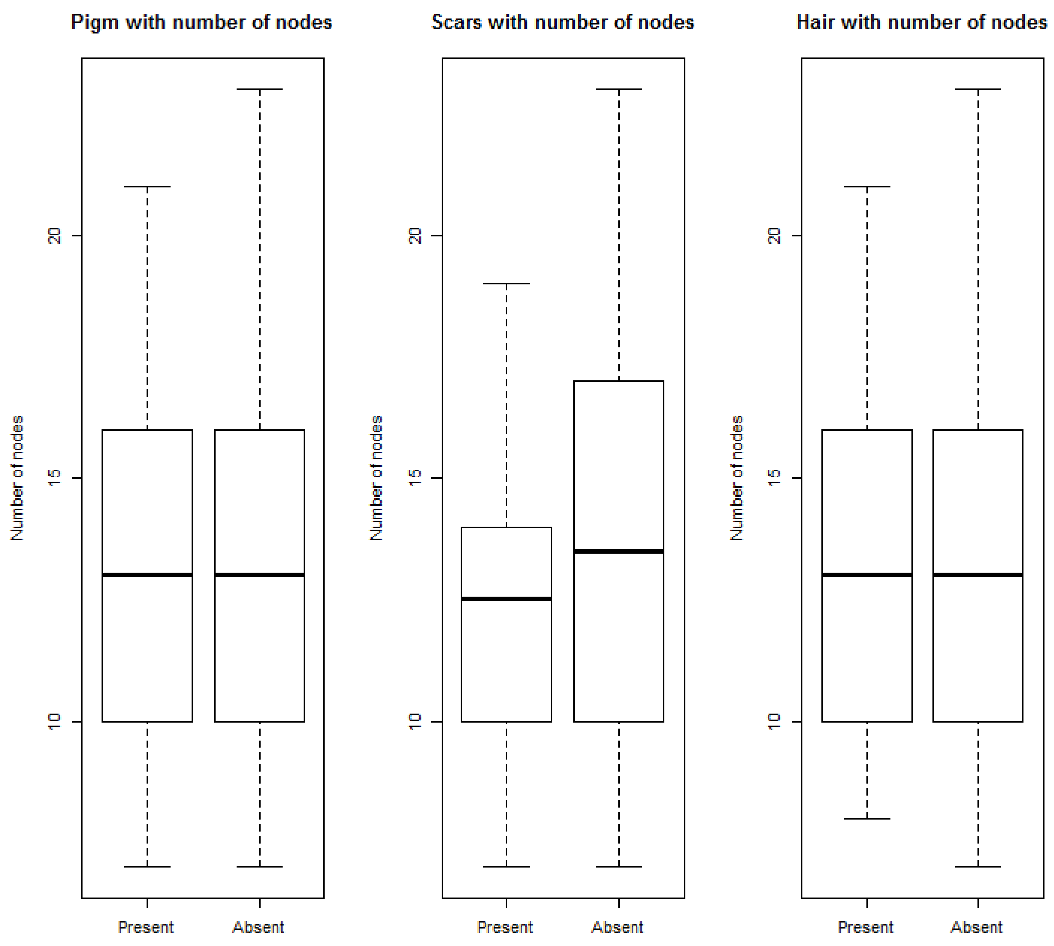


Figure 8.1 The association between the number of nodes and surface features at 9 mp, clenched position.

Number of edges and surface features

ANOVA testing supports the hypothesis and shows that there were no statistically significant relationships between the number of edges present and pigmentation, scars or hair (Figure 8.2, Table 8-3).

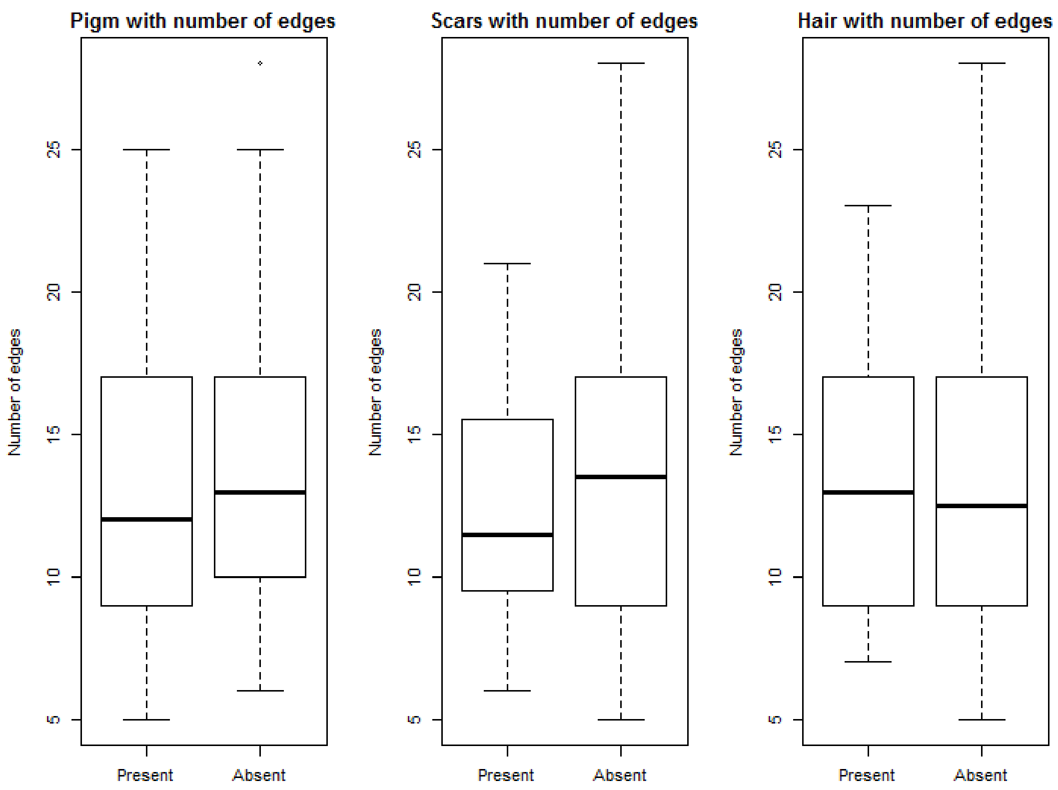


Figure 8.2 The association between the number of edges and surface features at 9 mp, clenched position.

Table 8-3 Table showing the p values from ANOVA tests for the number of nodes and edges with the presence of surface features.

Surface feature	**Number of nodes**	**Number of edges**
Pigmentation	0.875	0.924
Scars	0.09	0.073
Hair	0.53	0.65

8.2.2 Feature combination

This section explores combining two, previously independently assessed variables; vein network features and anatomical surface features to assess the variation of combined anatomical features in a multi-modal approach.

To establish the extent to which vein networks and surface feature information can be used together in a multi-modal approach to identification, it is important to ascertain the combinations of these features that represent the highest discriminatory capacity; e.g. the combinations of features that were not observed on the current database or those that were extremely rare. It is equally important to ascertain the most common combination of features.

Out of the 288 possible combinations considering all 7 variables (see section 8.1.2), only 61 were found on the sample dataset; this equates to only 21% of possible combinations, meaning that a total of 227 feature combinations were never observed in the sample (Figure 8.3).

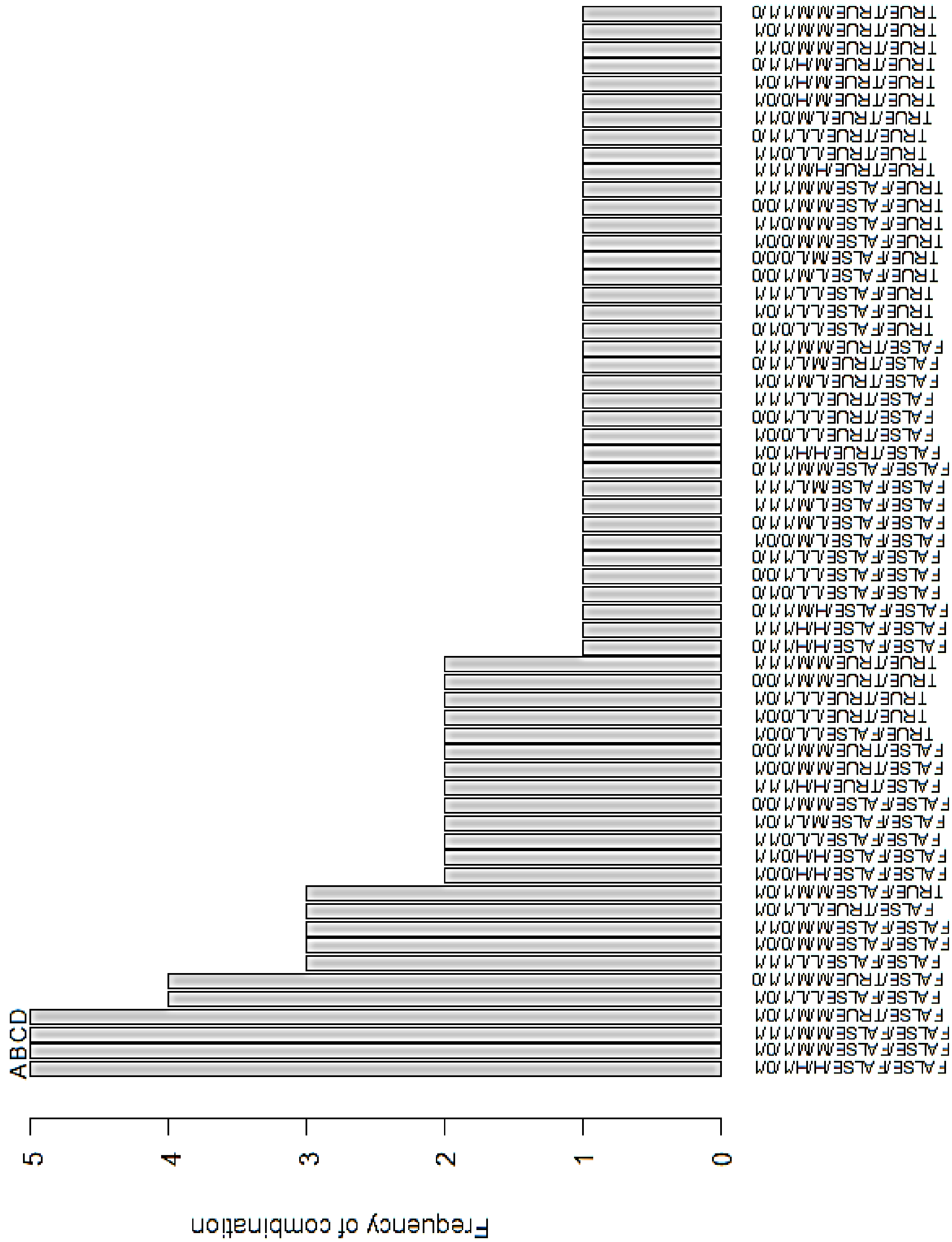


Figure 8.3 Chart showing the prevalence of all possible feature combinations (cases that did not occur not shown). X axis: the combination of features as described in Table 8-2 ; Y axis: the frequency of each combination within the database.

The majority of combinations only occurred once (37 occurrences). The most prevalent combination of features, of which there were 4, each occurred 5 times; this equates to 4.7% of the sample population. The details of these combinations are shown in Table 8-4 for clarification.

Table 8-4 Combination details for the most prevalent cases.

Prevalence	**Code**	**Intersections**	**Loops**	**Edges**	**Nodes**	**Pigm.**	**Scars**	**Hair**
5x	A	Absent	Absent	High	High	Present	Absent	Present
	B	Absent	Absent	Medium	Medium	Present	Absent	Present
	C	Absent	Absent	Medium	Medium	Present	Present	Present
	D	Absent	Present	Medium	Medium	Present	Absent	Present

All of the most commonly occurring combinations shared similarities, highlighting that the absence of intersections and the presence of pigmentation and hair comprise the most common set of features.

Three out of four of the most prevalent combinations contained no loops (with the exception of combination D), had a medium range of edges (9 – 16 edges) and nodes (10 – 15 nodes) (with the exception of combination A), and no scars (with the exception of combination C).

To contextualise this, Figure 8.4 shows an example of a hand image containing the combination of features as shown as ‘D’ in Figure 8.3.

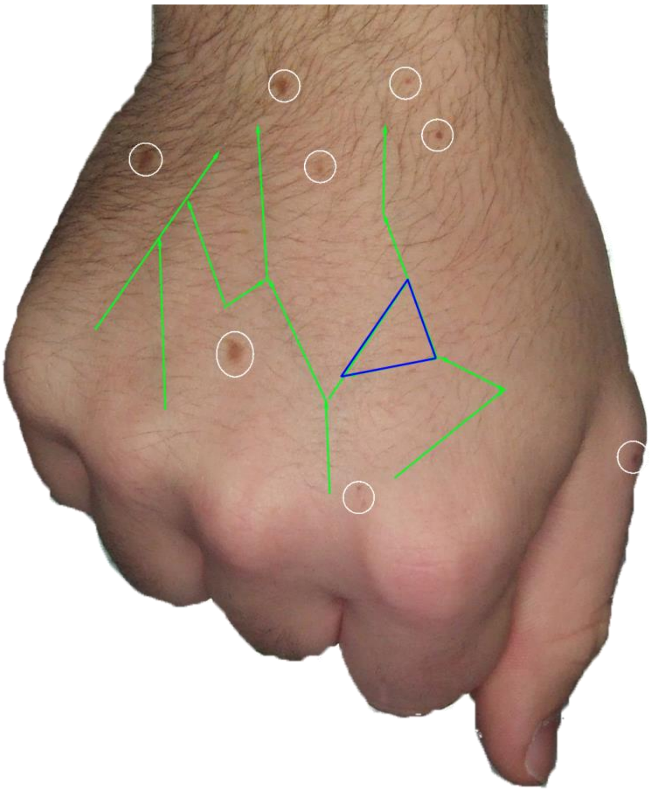


Figure 8.4 Example of the combination of features (D), containing: no intersections, a loop (blue triangle), a medium number of nodes and edges, pigmentation (white circles) and hair present, with no scars.

With the knowledge of which features were rarely seen, analysis of feature combinations was reduced to loops, edges, pigmentation, scars and hair only. Intersections were removed as they were not identified in the most prevalent combinations, and nodes were removed as they have been shown to be highly correlated with edges (Figure 6.19).

From this updated pool of features, there were a total of 48 possible combinations (Equation 8-2).

Equation 8-2: $Total\ number\ of\ possible\ feature\ combinations = 2^4 \times 3^1 = 48.$

Thirty-three of 48 possible combinations were found to be present in the sample (69%) when 5 variables were considered. The most common combination was identified 10 times, which comprised: no loops, a medium number of edges (9 to 16), pigmentation and hair present, with no scars (Figure 8.5).

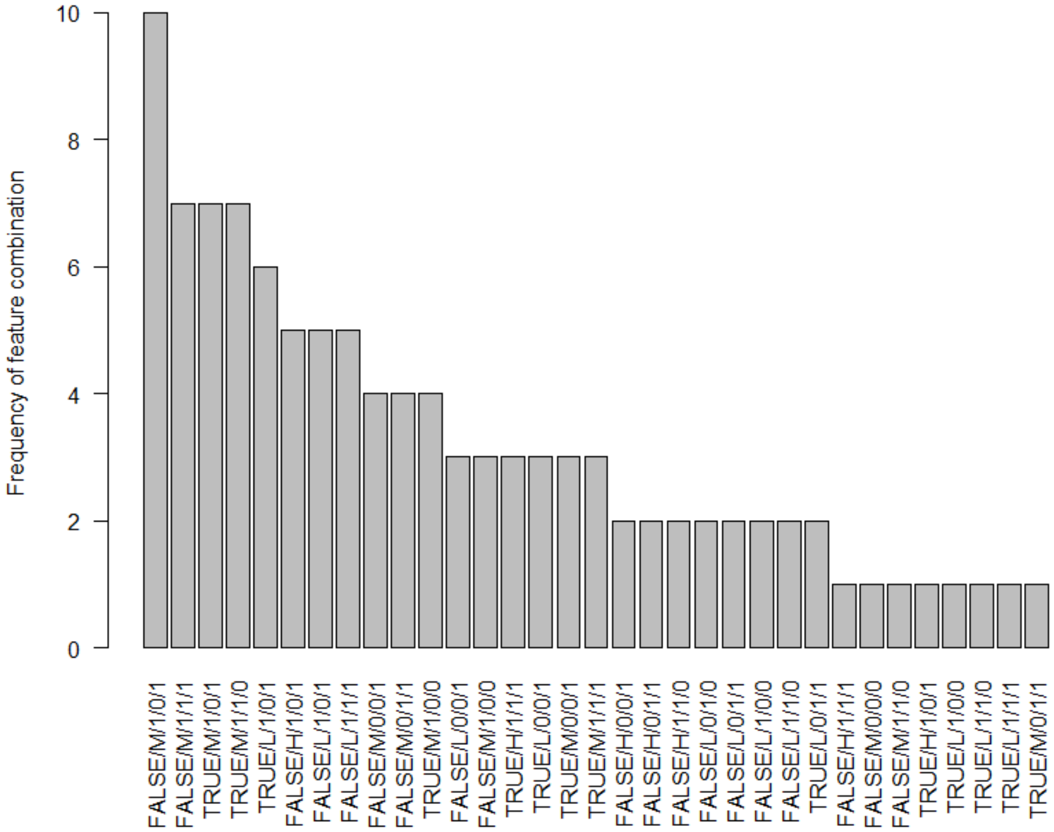


Figure 8.5 Chart showing the frequency of combinations considering loops, edges, pigmentation, scars and hair only. X axis: the combination of features as described in Table 8-2 ; Y axis: the frequency of each combination within the database.

The pool of features was further reduced by removing loops, as these were found to be absent from the most commonly occurring combinations in the previously reduced pool of features.

The remaining features to consider were edges, pigmentation, scars and hair. A total of 19 combinations were observed out of total possible combinations of 24 (79%) when 4 variables were considered (Equation 8-3).

Equation 8-3: $Total\ number\ of\ possible\ feature\ combinations = 2^3 \times 3^1 = 24.$

The most common combination was identified 17 times; this comprised medium number of edges (9 to 16), pigmentation and hair present, but no scars (Figure 8.6).

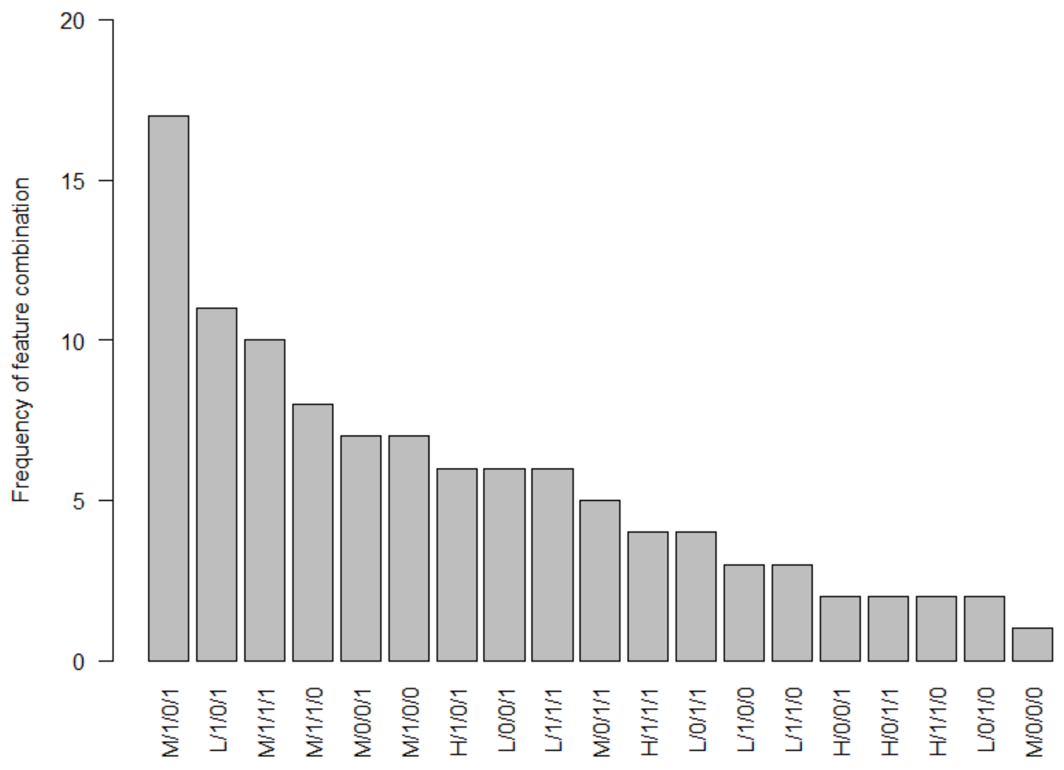


Figure 8.6 Chart showing the frequency of combinations including edges, pigmentation, scars and hair. X axis: the combination of features as described in Table 8-2 ; Y axis: the frequency of each combination within the database.

From these assessments it can be seen that when more features are considered, the total number of combinations observed is low with regards to the total potential combinations. Conversely, when fewer features are considered, it is more likely that more feature combinations will occur. This is summarised in Table 8-5.

Table 8-5 Summary of how reducing the number of features considered, increases the frequency of combinations.

Variables	**No. of variables**	**Possible combinations**	**Actual combinations**	**% of possible**
Edges Nodes Islands Intersections Pigmentation Scars Hair	7	288	61	21%
Edges Islands Pigmentation Scars Hair	5	48	33	69%
Edges Pigmentation Scars Hair	4	24	19	79%

The most common features have been explored. From the full list of variables, it was shown that 227 combinations were never observed on the sample dataset. As it would have been difficult to illustrate all 227 possibilities that were never encountered, examples of 2 of these are shown in Table 8-6.

Table 8-6 Table showing examples of two combinations of features that were never observed on the sample dataset.

Intersections	**Loops**	**Edges**	**Nodes**	**Pigm.**	**Scars**	**Hair**
TRUE	TRUE	High	High	Present	Present	Present
FALSE	FALSE	Low	Low	Absent	Absent	Absent

8.3 Feature combination study discussion of results

It should be noted that the statistical power of the analysis performed in the feature combination study was limited, due to the fact that the sample size was 106, and given the total combinations is little over double this value, it is likely that not all feature combinations will have occurred in the sample, or that the prevalence of some may be skewed. Despite this, the findings from this study contribute to the current literature, as the investigation of multiple features has not been assessed in this manner, for the purpose of forensic investigations.

Feature dependency discussion

It was important to ascertain whether the presence of any of the features were dependant, as this would provide a descriptive overview of what can be expected when presented with the assessment of hand images for forensic purposes.

The number of nodes and edges were chosen to perform this assessment as they provide a general indication of the overall complexity of a vein network. It was found that, as hypothesised, there was no significant interaction between the nodes/edges and each of the surface features (pigmentation, scars and hair) (Figure 8.1, Figure 8.2, Table 8-3). The lack of apparent feature dependency suggests that all combinations of features were potentially possible.

Feature combination discussion

From a review of the relevant forensic case work undertaken at CAHId, it was found that the majority of cases involved the identification of an individual from digital images of the hand utilised six variables at once (Figure 3.16). Therefore this study was performed to establish the variability of multiple anatomical features when utilised to establish similarities and differences between suspect and offender images. This was important so that when presented with a particular combination of features, the likelihood of this occurring can be determined.

It was found, when assessing all anatomical information available in this study, that the most commonly occurring combination of features contained; no intersections, pigmentation and hair present, no islands (with the exception of one combination (D)), have a medium range of edges (9 – 17 edges) and nodes (10 – 16 nodes) (with the exception of one combination (A)), and no scars (with the exception of one combination (C)) (Figure 8.3, Table 8-4). Importantly, this occurred only 5 times in the current dataset, which equates to 4.7% of the sample. With the most prevalent combination occurring in less than 5% of the sample population, this give support to the individuating power of these features used in conjunction.

Further to this, these features were considered in a binary or tertiary format; whereas in a case scenario, detailed information regarding shape, relative size, relative location etc. would be used, thus enhancing the discriminatory capability.

The features that were found to be absent from the most commonly occurring combinations were systematically removed from the testing. This highlighted that as the number of features decreased, the prevalence of feature combinations increased, thus indicating that with fewer features, the individuating capacity is reduced.

The findings from this short study, although preliminary, support the suggestion from Hong *et al.* (1999), Jain *et al.* (2004a) and Mohammed *et al.* (2014) that a multi-modal system is superior to a uni-modal biometric system by increasing the discrimination between two individuals, shown by increased performance of biometrics systems in terms of FAR and matching scores.

Furthermore, due to the fact that the anatomical features described originate from different aetiologies, further supports their independence.

Where possible many features should be considered in forensic investigations, however in reality this will not always be possible, as some individuals may not possess a multitude of features for which to utilise. Additionally, this raises the issue of, when presented with a small number of features in a forensic case, the practitioner should proceed with caution. This raises the question; what, is the minimum number of features required to provide adequate discrimination?

This short study set out to illustrate how utilising multiple anatomical features for the discrimination between two individuals can increase the potential of discrimination between two individuals. This approach is already employed in forensic investigations, but has never been quantified in this manner. The results from this study show that multiple features can be more discriminative than fewer, which should be of use to forensic practitioners when presenting cases where multiple features have been utilised. Future studies would benefit from extending the sample size, which may introduce more combinations observed, as well as introduce other features (such as skin creases). Furthermore, it is hoped that future research will expand on this data to extrapolate likelihood ratios which can then be presented to the courts in a comprehensible manner.

9 WIDER CONTEXT DISCUSSION AND CONCLUSION

The central aims of this thesis cover four key areas of consideration for the use of anatomical features as an aid to forensic human identification:

Reliability and repeatability: As with all emerging forensic techniques the reliability and repeatability of the method must be determined. This was established with regard to data extraction from visible light images of the dorsum of the hand; specifically the superficial vein pattern and anatomical surface features.

Population Distribution: To facilitate an understanding of the variation of these features in a sample population, the distribution of features in standardised conditions was explored. Furthermore, the influence of selected biological characteristics on the distribution of features was assessed.

Application: To contextualise this information in relation to relevant forensic case work, tests were conducted to investigate how robust the identification of vein pattern and surface features are when assessed in images of poor quality, compared to a standardised image.

Multiple Aetiology: To establish whether assessing all information from all feature groups improves discriminatory capability of anatomical features of the dorsum of the hand for forensic human identification.

The overriding aim was to provide support for image assessment and anatomical feature analysis in cases of Child Sexual Abuse (CSA), in which images commonly depict only the hand(s) of the offender.

With these objectives in mind, this chapter will discuss the applicability of utilising superficial vein patterns and other anatomical features to aid identification in cases of

CSA. Furthermore, it will address how the introduction of a new statistical approach for the quantification of the vein pattern can enhance the use of Vein Pattern Analysis (VPA) for forensic purposes, with consideration of legal admissibility requirements for emerging forensic techniques.

9.1 Relevance of the research

Cases of CSA are an increasing issue for police authorities. It cannot be known whether this is due to increased awareness of such crimes, resulting in increased reporting, or changes to legislation with regard to the categorisation of such crimes (Grubin, 1998; Harker *et al.*, 2013; Jutte *et al.*, 2014), nevertheless the statistics show that more cases of this nature are being presented to police and forensic agencies. A portion of these cases contain imagery that necessitates presentation to the analysis team at CAHId.

CSA is probably unique as a crime, as the offender intentionally captures themself committing the offence and thereby providing an opportunity to utilise potentially discriminative information contained within such images, as a means of identifying the victim and/or the perpetrator. The images presented to CAHID usually contain a region of the perpetrator's anatomy, most frequently the dorsum or semi-pronated region of the hand (Black *et al.*, 2009; Meadows, 2011; Ferguson and Raitt, 2013).

The investigation of sexual abuse crimes through the examination of anatomical information from digital images was introduced to the UK courts by CAHId and the National Police Improvements Agency (NPIA) in 2007. Investigation is based on establishing similarities and differences between anatomical information seen on the offender within the image, and images of the suspect which are generally captured in the custody suite (Meadows, 2011). This approach does not attempt to identify, but more importantly seeks to establish whether a suspect may be eliminated from the investigative process or whether there is strength in the degree of similarities visible. In some cases, the similarities may be too great to confidently exclude the suspect, leaving the finder of facts (the jury) to decide the weight to be applied to this evidence (Ferguson and Raitt, 2013) although guided by the experts. The strong anatomical underpinning of this approach permits admission of this evidence, as the subject matter is part of a recognised body of science or experience (Davidson, 2007; Sinclair, 2013). Furthermore, this approach provides a powerful evidential statement, however in terms of the admissibility requirements of emerging forensic techniques; further research is required to establish the validity and repeatability of this method.

The impetus for this research is to develop vein pattern quantification to establish statistical support, as generated by empirical data and to illustrate the use of multiple features as a means of increasing discriminative capability.

Network Analysis (NA) of the vein pattern was selected as a novel method for quantification of the vein pattern. NA is a form of multivariate statistical analysis that uses a collection of objects (nodes) and their inter-connections (edges) to describe the overall structure of a complete unit; termed a network. This approach is established on strong mathematical foundations and theories, and has been gaining popularity in its application to life sciences and engineering (Alon, 2007; Koch, 1999; Maslov and Sneppen, 2002; Milo et al., 2002; Montoya and Ricard, 2002; Newman, 2001; Shen-Orr et al., 2002; Szallasi, 1999).

NA allows rapid analysis of large databases, vital in modern science with increased availability of data through the advancement of computer aided technology.

It should be noted that, although the use of network analysis may have hindered the extent of statistical analyses that were conducted in this research, this research has introduced the potential of how network analysis can be applied to vein pattern analysis and therefore this research should be seen as an introduction to further studies, where the potential of NA can be explored fully.

9.2 Summary of major findings

The results from statistical testing pertaining to each of the aims of this research have been discussed within the relevant sections (see chapters 0, 7 and 8). This section will contextualise the results further in light of the provision of support for forensic practitioners to develop current methods of forensic human identification.

The results will be summarised in four sections; 1) observer reliability and repeatability studies for both vein patterns and surface features; 2) variation in vein pattern features and surface features, in standardised conditions and the effects of selected biological characteristics, 3) variation in vein pattern features and surface features when controlled variables were introduced (position and image quality) and 4) efficacy and individuating capacity of vein pattern and surface features when assessed in combination.

9.2.1 Observer reliability studies: vein pattern and surface feature data extraction

The aim of this study was to determine the reliability of the methods used to extract data from digital images of the dorsum of the hand, relating to the superficial pattern of veins and anatomical surface features for quantification.

Existing methods of vein pattern assessment, established by Meadows (2011) were employed for the first stage; subsequent stages were further developed to enable examination of data through network analysis, therefore only the novel application of network analysis was tested for inter and intra-observer reliability.

The purpose of the observer studies was not to establish whether the manual tracing of the networks was repeatable (as this was explored by Meadows (2011)), but that the network information could be extracted in a reliable and repeatable manner.

Surface feature data extraction has been investigated in greater detail by Macdonald-McMillan (2011) whilst, for the purpose of this research, only information relating to presence or absence was required. However, the novel method of surface feature data collection differed from previously tested methods and observer studies were conducted accordingly.

Superficial vein patterns: Intra-observer Study

Overall the single observer (author) was repeatable in their reproduction of the same network on several occasions, although it was discovered that some of the visual traces appeared inconsistent with the network after it was recorded in R©. Although this was identified as a source of error, it should be noted that the precise location of the 'edges' in the linear trace were not always indicative of the final topology of the network when transferred into R© (Figure 6.10). The 'linear trace' stage of data extraction provides clarification to the observer of feature points (nodes), whereas it is the recording of the labelled nodes, which translate directly into the final topology of the network when assessed in R©. Therefore it is the translation of the node labels that are key to ensuring the network is recorded repeatedly. This is the proposed reason as to why visual and statistic approaches did not always report consistent outcomes.

When considering the R© composed version of the network, it was found that vein networks were repeatedly recorded with regard to motif structures (Figure 6.11, Figure 6.12), intersections (Figure 6.14) and loops (Figure 6.15), irrespective of network complexity. It is thought that this high level of performance may be due to the author having awareness of the methodology, throughout development, as well as having experience of tracing the vein networks in the prescribed manner for 636 images. Alternatively, it is hypothesised that the method of extraction was robust, and repeatable.

Superficial vein patterns: Inter-observer

The inter-observer study establishes whether other individuals can perform at the same level of repeatability and reliability as the author, plus investigates the effect of experience on the reproducibility of vein networks.

Reproducibility was assessed by comparing observer traces to a 'reference' network, selected from the traces completed by the author. The definitive vein pattern cannot be known as it resides beneath the skin; the traced version is the perceived pattern, according to the observer. This method of comparing traces to a reference network was deemed appropriate as the author was consistent in reproducing the network (see section 6.3).

The reference network was selected at random after testing of several repeats (by the author) of the same network; this showed that with only minor fluctuations, the results were consistent. It would have been possible to compare all observers against one another, in a pairwise comparison approach, however this may have confounded errors from observers, therefore it was more reliable to compare observer trace to a trace from an observer of known error.

Overall, and somewhat expectedly, it was found that simple networks were more consistently reproducible, but moderate to more complex networks were more difficult to reproduce repeatedly.

Each observer had no training or direct experience in applying the methods utilised in this study, with the exception of the instruction manual with which they were provided. It was therefore of value to assess whether any improvement was observed in the observers performance during the study.

To assess the level of training required for an observer to reproduce the reference network correctly, the levels of prior experience (such as qualifications and professional experience) were examined, to establish whether certain skills were important in performance of this task. Observers were requested to self-assign their level of experience graded in four key areas; anatomical knowledge, experience of hand feature analysis, operation of R© software and the operation of Adobe® Photoshop®. Individuals were asked to self-assess their level of experience as; none, minimal, moderate or extensive.

It was found that there was no statistically significant relationship between the performances of the observers and their level of anatomical knowledge, experience of hand feature analysis, operation of R Studio© or experience of Photoshop (Figure 6.18).The sample size was small, even smaller were the number of observers within each experience category, therefore challenging the interpretation of statistical analyses (Table 6-7).

It is recommended that future studies should expand by utilising more observers, with a broad range of experiences, but also with many observer of similar experience, so that robust statistical analyses can be performed.

When considering the differences in performance of author and untrained observer, a relationship between network complexity in the inter-observer study was elucidated; when presented with simple to intermediate level networks, little training was required to enable the observer to identify the features, however when presented with networks of high complexity, observers with little experience or training struggled to repeat the network. The opposite was indicated in the intra-observer study, where the percentage of isomorphic networks increase with each level of complexity (sparse 50%, intermediate 62%, dense 66% isomorphic networks in relation to detection of 3 and 4 node motifs, although the difference between each complexity was low. This may indicate that with extensive experience of applying the method (author), the observer can reproduce repeatedly the networks of any complexity, where observers who had only completed 20 traces were not as competent. Meadows (2011) found significant differences in observers carrying different levels of experience, and that experience in anatomy, vein pattern analysis for forensic purposes and Photoshop were attributes of the most reliable observer.

To examine fully this methodology, future studies should expand to include a complete manual tracing element (which was removed from this study, to only focus on the extraction of data for the purposes of network analysis) and increase the number of observers in total and or each experience category.

Surface feature: Intra-observer

Anatomical surface feature information was recorded, primarily to be used in conjunction with the vein network data, in the 'Feature combination study' (chapter 8). Therefore the recording of this information was somewhat simplified in relation to similar studies (Black et al., 2014a, 2014b; Macdonald-McMillan, 2011). For the purposes of this research, only the presence or absence of three anatomical surface features was considered; isolated areas of pigmentation, superficial scars and hair patternation. Nevertheless, to confidently proceed with the data in subsequent aspects of the research, the reliability of extracting the surface information in this way must be established.

The author was found to be repeatable in the extraction of pigmentation, scars and hair as the differences between repeats were found to be insignificant (Table 7-3). However, this performance may be due to the simplification of the task, whereby specific physical details were not required for each feature. Despite this assumption, the findings from this study are comparable with the findings of Macdonald-McMillan (2011); in this study the features were considered in more detail, including number, size, orientation etc. and found that differences between repeats of the same observer, overall did not varying significantly, with the exception of the number of ephelides, and the number of orientation ‘category 1’ scars.

Surface features Inter-observer studies

To reiterate, surface features were recorded in a simplified manner however, it was still necessary to establish how repeatable these features were when recorded by observers of varying levels of experience.

Despite minor trends in agreement/disagreement in the number of images with pigmentation, scars and hair patternation, it was concluded that there were no statistically significant differences between any of the observers (Table 7-7). This result agrees with the findings from the intra-observer study, and again performance may be indicative of the simplification of the methodology, as the results of the current study do not agree with the inter-observer study conducted by Macdonald-McMillan (2011); differences between observers, was significant with regard to the number of features identified, particularly between three observers with differing levels of experience. Differences were mostly seen in the number of ephelides, which are often present in high numbers.

Despite this, for the purpose of this study, the observer study results indicate that if only the presence or absence information is required, this is a repeatable method. It should be borne in mind that when assessing these features in a forensic scenario, more detail is required with regards to physical description and relative location of features.

Importance of establishing observer reliability in the context of legal admissibility requirements

Ascertaining the validity of an innovative forensic technique is vital to its acceptance in legal proceedings (Dror *et al.*, 2006; National Research Council of the National Academies, 2009; Page *et al.*, 2012). Increasingly, it is advised (and in some jurisdictions enforced) that the validity and reliability of forensic methods are explicitly reported along with expert opinion evidence (Association of Forensic Science Providers, 2009; National Research Council of the National Academies, 2009).

The impact of lack of research to establish and qualify the validity and reliability of forensic disciplines was highlighted in cases as far back as Frye (Frye vs. United States 293. F 1013, 1923), and as recent as R v Dallagher (2003) and McCreight v HMA (McCreight v HMA HCJAC 69, 2009).

It is understood that the human observer will show inherent subjectivity in their assessment of a pattern, and can never be entirely objective. However, with the current lack of automatic approach to extract patterns, the level of variation in the way a human observes a pattern must be established. It is important, when presenting data relating to VPA and other anatomical feature analysis that the level of error is reported clearly to maintain transparency in the methodology (Doyle and Doyle, 2012).

This research has gone some way to address these overriding issues with regard to the identification of individuals from digital images. Results from both the inter- and intra-observer studies support the overall stability of the methods used to extract vein pattern and surface feature information. However, it was highlighted that the complexity of the networks affected the level of reliability, with increased complexity showing a reduced rate of reliable reconstruction of the network.

This results is comparable with a recent study by Pearson (2014) who investigated the difference in ability between the trained expert, and the untrained observer to identify an image of a hand, from a pool of potential matches correctly. It was found that although the trained observers would rely on features with known discriminatory capabilities, the overall results showed that there were no significant differences in the responses from an untrained or expert observer. In summary, it appears that the trained observer has the experience to know which features to rely on, in terms of their discriminatory capabilities, whereas an untrained observer is likely to rely on less definitive observations such as skin tone. With regards to vein pattern extraction, simple networks are reproduced by both groups, whereas the trained observer was more capable when presented with complex networks.

The issue of observer bias is only touched on in this thesis but it is important to note that it is inevitable that an examiner will in some way be biased; studies have shown that due to the disturbing and emotive nature of material assessed in the cases, it is thought that practitioners involved will be subconsciously more susceptible to observer bias (Dror *et al.* 2005). Despite the fact that observers were shown to be repeatable in this study, the test scenario did not truly reflect a case scenario, where the user would be aware of the heinous circumstances of the case and therefore the results from the study cannot truly represent how an expert would perform in a real case scenario.

It is hoped that the findings of this research and others (Meadows, 2011; Macdonald-McMillan, 2011), will clarify the reliability of the methods outlined in this thesis and act as a support of this approach in the legal framework. Due to the fact that this study was the first of its kind to introduce network analysis of vein patterns, the research is introductory, and future studies would benefit from an expansion of the current study to enable more robust statistical testing of the methodologies. However it is appreciated that eliminating human error is ultimately impossible due to the subconscious mind. To eliminate this effect entirely, automation of methods would have to be explored.

9.2.2 Variation in vein network and surface features in standardised conditions, and in relation to biological characteristics

This section will summarise the results pertaining to establishing the variation of vein network features and anatomical surface features across the sample population, and how selected biological characteristics may influence this distribution.

Vein network features: Variation in standardised conditions

It is important that forensic practitioners involved in establishing similarities and differences between two individuals based on the superficial veins on the dorsum of the hand, have an understanding of the expected variation, (i.e. the normal level of differences that can be expected in this region); this increase in awareness will assist in the evaluations as to whether two sets of images belong to the same individual. Additionally, it is important for the practitioners to have access to a suitably large database of hand images, on which they can compare their findings, and estimate the likelihood of the pattern in question, occurring. It is for these reasons that this aspect of the study was conducted.

It was found that the most common density of a network, in terms of the number of nodes and edges, contains 8 to 16 edges (55 networks) and 9 to 15 nodes (57 networks). Fewer networks fall into the category, termed ‘dense’, and containing 16 to 28 edges (28 networks) and 15 to 24 nodes (29 networks), whilst fewer still are categorised as ‘sparse’ and contain 0 to 8 edges (23 networks) and 0 to 9 nodes (20 networks) (Table 6-9).

In addition to feature counts; this study considered the way in which features of a vein network are connected, therefore providing more detailed information regarding the topology of the network. Feature counts, although useful in terms of pattern density, are referred to as ‘induced sub-graphs’ in relation to network analysis, whereby two structures are mathematically identical, or have exactly the same feature count, but the topologies can differ (Tran *et al.*, 2014); this is why it is important to consider more than feature counts as this is not entirely representative of the pattern or network as a whole. This information originates with the motif data; sub-graphs that interconnect to form a larger network. It was found that some motifs were more common than others; for example a simple 3 node arrangement (motif A) was identified in 100% of networks in the sample dataset, whereas a 3 node loop, with only 1 edge difference to A, was found in 20% of the networks (Figure 6.24). However, this data is difficult to interpret, as motifs cannot be considered in isolation. They exist only as part of a larger structure, where they are usually connected with another motif. For example, refer to Figure 6.7 to visualise how motifs can be deconstructed from larger units. Despite this, it can be seen that as the complexity of motifs increase, their prevalence decreases. Therefore if a complex arrangement is identified within a network, it is more likely to be rare and therefore provide more discrimination between two networks, than a simpler motif.

The majority of the sample contained no loops (59.4% of networks); whilst one loop was found to be present in 29% of the sample. Shorter loops (3 nodes) were more common than larger loops (5 node loops) (1x 3 node loop present in 16%, while 1x 5 node loop present in 11.3%) (Figure 6.28). Intersections were found to be marginally less common than loops, and similarly the majority of the sample contained no intersections, whilst 25% of the sample contained one intersection.

In an attempt to explain this level of variation in the pattern of superficial veins, the embryological and anatomical literature was examined. The way in which blood vessels develop, through the coalescing of blood islands, suggests there is no strict pathway to direct the development of the capillary network (Larsen, 1993; Eichmann *et al.*, 2005; Sadler, 2012). There are many suggestions as to what regulates vascular growth and these include pH levels, hypoglycaemia, mechanical stress from proliferating cells and immune responses to hemodynamic forces after the onset of the first heartbeat (Tomanek, 2002). These circumstances vary between individuals, perhaps indicating that vascular growth is a process unique to the set of circumstances at a specific stage of development; thus explaining the observed level of variation. This can only be regarded as a theory as how vascular patterns are determined, remains largely undetermined.

With regards to adult anatomy, there is a scarcity of detailed description of the superficial veins of the dorsum of the hand, other than the generalised term in reference to the area between the metacarpo-phalangeal joint and the wrist, as the ‘dorsal venous network’ (Bergan, 2007; Cunningham and Robinson, 1918; Gray, 1918), a vague term that does not attempt to describe the pattern created by the branching veins, perhaps an indication that no precise description can be obtained due to the high level of variability.

In addition to general distribution of the vein network features, it is useful to be aware of any statistical relationships that exist between the presence of vein network features and biological characteristics of the individual. It was found that there was no significant relationship between the number of nodes or edges in a network and the age, weight, or body side of the individual. There was a significant relationship found to exist between the total body fat percentage of an individual and both the number of nodes ($p = 0.017$) and edges ($p = 0.042$) (Table 6-20), however, the correlation was weak ($r = -0.23$ (nodes) and -0.197 (edges)).

This is thought to be due to the layer of subcutaneous fat overlaying the veins causing the pattern to be partially obscured. It is noted that no significant relationship was discovered between weight and the number of nodes or edges found. Weight accounts for the whole body mass including bone, muscle, water etc., therefore is not representative of the amount of subcutaneous fat an individual possesses. The difference in results for weight and body fat percentage show that these two parameters affect the vein pattern visibility differently; an individual who may be heavy in terms of overall weight may have visible veins, whereas it is likely that an individual with a high body fat percentage is likely to have a lower number of vein pattern features than someone with lower body fat percentage. Other studies have also suggested that increased levels of subcutaneous fat may obscure the superficial veins (Chiao et al., 2013; Zharov et al., 2004).

Surface feature variation: Variation in standardised conditions

Pigmentation was found to be present in 72.6% and scars in 43.4% of the sample population. As previously mentioned, the means of data collection in this study was simplified so that this data could be combined easily with the more complex, vein network data. Whilst the data described will be of added value to the forensic practitioner in terms of an indication of distribution across a sample, other studies have provided more in-depth descriptions of the variation of surface features (Black et al., 2014a, 2014b; Macdonald-McMillan, 2011).

Hair on the dorsal surface of the hand is a universal trait (Szabo, 1967), however it is not clearly visible in all individuals. Results indicate that 25% of individuals within this dataset have no visible hair. The current study does not account for the density of hair, and it is thought that collecting hair patternation information with the use of gradation would be more informative.

The effects of biological characteristics on the surface features identified were tested, and it was found that no statistically significant relationship existed between the weight, body fat % and body side of the individual. There was no association with age and pigmentation or scars, but a significant relationship was found between age and the presence of hair.

This information will allow practitioners to assess the likelihood of features occurring in suspect and offender images, with the support from tested databases. This will allow practitioners to provide more supportive evidence for their reporting of the assessment of anatomical features in the dorsum of the hand. Data extracted from tested databases to support expert forensic evidence has been suggested as a requirement to verify the applicability of forensic techniques (Association of Forensic Science Providers, 2009), therefore this research goes some way towards fulfilling this requirement.

9.2.3 Variation in vein network and surface features: hand position and image quality

This section will address the results pertaining to the investigation of robusticity of the vein network and surface features when assessed in images of poor quality. Variations of image quality were assessed to investigate data loss between a police custody image (example of 'good quality') and an offender image (example of a 'poor quality'). Positional changes were considered to investigate the expected data loss between a standardised, database image (or police custody image) to a non-standardised, (offender) image, where the hand is observed in a functional position.

Vein patterns variation due to changes in hand position and image quality

The position in which the hand was photographed significantly affected the observed number of nodes and edges, with the clenched (standardised) position showing more information than the semi-pronated position; an average of 5 nodes and 5 edges difference. Loops were more frequent in the clenched position, compared to the semi-pronated position, and intersections were also more frequently observed in the clenched than in the semi-pronated position.

Image quality was also shown to affect the number of nodes and edges detected in a vein network, with the Fujifilm 9 mp showing the greatest volume of information, followed by the Fujifilm 0.3 mp, with the mobile phone images showing the least information.

When considering the number of loops and intersections, it was found that the presence of one feature (loops or intersections) was most common in the highest images quality (Fujifilm 9 mp), followed by the Fujifilm 0.3 mp, with the mobile phone images showing the least. However, when considering the presence of more than one loop or intersection (2 or 3 loops or intersections) it was found that this pattern was reversed to Fujifilm 0.3 mp > Fujifilm 9 mp > mobile phone.

When considering motif identification, 3 out of the 7 motifs detected were found mostly in the Fujifilm 9 mp, followed by the Fujifilm 0.3. mp, and lastly the mobile phone; 2 out of the 7 were found in equal quantities in the 9 mp and 0.3 mp, with the least found in the mobile phone.; a further 2 out of the 7 were found most in the 0.3 mp, followed by the 9 mp and least in the mobile phone images (Figure 6.46 and Figure 6.47).

The mobile phone images consistently reported the lowest volume of information, with the Fujifilm (either at 0.3 mp or 9 mp) reporting the highest. The mobile phone resolution at <0.2 mp was comparable with the lowest setting on the Fujifilm, so it is therefore indicative that it is not the resolution alone that may affect the level of detail seen within the image, possibly other factors, such as the lens of the camera. The lens on the Fujifilm was a Fujinon 10.7× optical zoom lens, and while the mobile phone lens information is not disclosed, it is apparent from visual examination that is it not as technologically advanced as the DLSR camera. Despite the fact that the mobile phone used in this study may now be regarded as ‘out-of-date’ in a rapidly advancing technological age (with current market leading mobile phones ranging from 16 mp to 41 mp cameras (Microsoft, 2015; Samsung, 2015), this study has highlighted that the restricted lens contained within a camera phone, cannot match its counterpart in a DSLR camera. Currently, the majority of images are captured on a mobile phone; 60.1% of the human population is estimated to own at least one mobile phone, and 83% of those contain a camera phone (Ahonen and Moore, 2013). More than 90% of all humans who have taken a picture have only done so on a camera phone and not on an actual camera (Ahonen and Moore, 2013). Although the mode of image capture is not always disclosed in forensic cases, it may be suggested that images are likely to have been captured on a mobile recording device. As the results from this study show, despite rapid advancement in resolution the mobile phone still produces images of lower quality than the cameras tested in the current study. In addition to this, many of the forensic cases are historic and therefore being faced with images of differing quality will remain an issue.

When both hand position and image quality were assessed together, it was found that changes in resolution resulted in the most data loss, followed by the changes in position. The clenched position consistently reported more details of vein patterns than the semi-pronated position. The anatomical literature was sought in an attempt to understand this result. With regards to the development of the upper limb, during embryological development the rotation of the primordial limb, and specifically the thumbs, from their alignment with the rest of the digits, to its adult location, may be important in the appreciation of the arrangement of superficial veins in the lateral aspect of the hand, the area most visible in the Sp position. Fewer veins were also found in this region by Donnelly (2014).

Further to this argument, clarification as to why fewer vein network features were visible in the semi-pronated position compared to the clenched position could be sought from the underlying anatomy of the hand. The region visible in the Sp position is the lateral region of the hand, most prominently the thumb and surrounding area. It is known that deeper anatomical structures differ in this area compared to other regions of the dorsum of the hand, in that the lateral portion is mostly soft tissue, as opposed to bony, hard structures in the central to medial aspect. The underlying anatomy may determine how visible the veins are; when overlaying hard surface they are more apparent, whereas when overlaying a softer surface they tend to be less visible.

Information relating to detail loss between a controlled and uncontrolled image (suspect and offender) will enable the practitioner to qualify their findings in light of image loss data; something which has previously not been available in a quantified manner.

There are few studies from the biometric literature with which to compare these findings, as this approach to identification has not been reported previously, and the use of vein networks in the biometric field are performed under standardised conditions, usually with precise directions on the location and positioning of the hand in the biometric system.

Surface features variation due to hand position and image quality

Changes in hand position were shown to have no statistically significant effect on the presence of pigmentation, scars or hair, whereas image quality was shown to have a statistically significant effect on all surface features. The number of images with features present decreased with decreasing image quality (Fujifilm 9 mp > Fujifilm 0.3 mp > mobile phone), with the exception of pigmentation in the clenched position (Fujifilm 9 mp > mobile phone > Fujifilm 0.3 mp) where the least information was seen in the Fujifilm 0.3 mp; although the difference between the mobile phone and Fujifilm 0.3 mp images was just 1%. Another exception was with the semi-pronated position regarding the presence of hair (Fujifilm 0.3 mp > Fujifilm 9 mp > mobile phone) although again the difference between the Fujifilm 9 mp and Fujifilm 0.3 mp images was just 1%.

In relation to the biometric literature, the exploration of these features has not been discussed widely, other than their potential to act as additional support to other 'classic biometrics'. The purpose of collection was to combine surface feature data with vein network data to establish whether a multi-modal system is more robust than a uni-modal approach in a forensic context, and therefore the relevancy of these features will be discussed in the following section.

9.2.4 Combining both feature groups to improve the discriminatory capability of using the dorsum of the hand for identification/exclusion purposes.

It has been recommended that the effectiveness of biometric systems can be further enhanced by the use of multi-modal systems, i.e. systems utilising more than one biometric feature (Hong *et al.*, 1999; Jain *et al.*, 2004a; Mohammed *et al.*, 2014; The Federal Bureau of Investigation, n.d.). Furthermore a multi-modal system using characteristics from more than one feature group are said to overcome the issue of using just one biometric trait (Lee *et al.*, 2008) (Hong *et al.*, 1999; Ross and Jain, 2004). A theme within the Horizon 2020 proposed funding opportunities for research and development includes the development of a multi-modal biometric system to enhance security across EU borders (European Commission, 2013), and is therefore an issue held in high regard with respect to border control and security.

Coupled with the suggestions from the biometric literature, the concept for current research is derived from forensic case work, which frequently involves the use of more than one anatomical feature in the investigation of establishing similarities and differences between two sets of images. From a review of the cases undertaken by CAHId, a single feature was assessed in only 8.6% of cases, and in the majority of cases, six feature types were used. This highlights that a multi-modal approach is already employed, albeit holistically.

It was therefore necessary to establish how two feature groups; superficial vein networks and anatomical surface features, affect the potential discriminatory capacity. It was hypothesised that using surface features in conjunction with vein networks would exceed the level of discriminatory power of vein networks or any of the surface features in isolation.

It is also hypothesised the features from varying aetiologies will enhance the discriminative power. It has been suggested that vein patterns are regulated by many factor including genetic and biochemical composition in the womb. Isolated areas of pigmentation have been shown to be regulated both by genetic and environmental factors, whereas scars are known to be accidental, and the presence of hair genetic (section 4.1).

The current study found that when the number of features used increased, the probability of finding individuals on the database that exhibited the same combination of features, decreased (Table 8-5); thus supporting the notion that many biometric traits are more discriminative than one.

This was also found by Hong *et al.* (1999), who reported that the false acceptance rates (FAR) for face recognition (15.8%) and fingerprints alone (3.9%) were out-performed by a combination of both characteristics together (FAR = 1.8%). Another example was shown by Mohammed *et al.* (2014), when testing finger vein and iris scanning techniques in conjunction, they were found to have a matching score level of 92.4% accuracy.

The combination of anatomical features has never been quantified in this manner for forensic purposes, and therefore this study contributes to the literature by illustrating that with a larger pool of anatomical features, the ability of the features to discriminate between two individual’s increases, due to the likelihood of their presence being reduced.

9.3 Relevancy of the findings in this research

This research, has introduced network analysis to the quantification of vein patterns for the purpose of forensic human identification. As a results, this research is multidisciplinary; encompassing influences from the biometric literatures (often which are conducted for commercial purposes); anatomy research (although there is a distinct paucity of research relating to variation of the superficial vein patterns in the hand); and finally, for the applicability of this research, the literature regarding the law and admissibility with respect to forensic expert evidence.

Some of the features investigated in this research are recognised as biometric traits and are utilised in commercial biometric systems. They are categorised within the ‘something you are’ level of authentication, which is considered to be more robust than other means of identification in that they are more resistant to fraud (Desmarais, 2000; The Biometric Consortium, 2006; Wilson, 2010). A biometric must exhibit certain criteria to ensure their applicability; universality, distinctiveness, permanence and ease of collection (Jain *et al.*, 2004b; The Biometric Consortium, 2006; Burghardt, 2009;). In relation to veins, every individual possesses a pattern of these in the dorsum of the hand (although the level to which these can be visualised varies between individuals) and thus can be classed as universal. The distinctive pattern of veins has been explored in this research (chapter 6), as has the means in which vein network data is collected from visible light images. Regarding permanence, this aspect was not investigated in this study, but others have shown the vein pattern to be stable over time (Wang *et al.*, 2008; Meadows, 2011).

This research is based on the application of biometric techniques to forensic human identification, utilising the anatomy that underpins this approach. However, the use of vein patterns as a biometric differ in their use in forensic investigations, in that biometrics are able to use live NIR imaging of the individual. This is not possible in a forensic scenario as images are previously captured and usually in visible light. Despite this, similar principles apply regarding methodology, and therefore the biometric literature was reasonable to refer to in relation to this research.

The specific methodology used to quantify vein patterns differs between the current study and biometric approaches in that a biometric system considers the overall pattern, whereas the current research is focussed on the individual features of the vein pattern and how these are connected, not the exact topology or precise location. This is partially due to the fact that new quantification methods were introduced during this research and therefore with the focus primarily of development of the method, a more general overview of the vein network feature distribution has been provided in this research. It is hoped that as network analysis has been shown to be a potentially valuable tool for vein network quantification, that future studies will explore this method in more detail with regard to vein network topology.

Biometric vein recognition systems have shown that a vein pattern can be used to 'identify' an individual with a high degree of accuracy. This is performed by establishing a threshold based on the similarities between the target image and all templates on the system, with the threshold formulated from large databases (Luo *et al.*, 2010; Wilson, 2010). A similar method was adopted by fingerprint examination through the application of the '16 point standard'.

Although this notion of reaching a threshold to qualify identification may be applicable and reasonable in a biometric system, it is apparent that this definitive approach is not relevant for the purposes of forensic human identification. Following the fingerprint inquiry in Scotland, the use of fingerprints in the identification of individuals involved in crime, has been downgraded from evidence of fact, to evidence of opinion, due to the level of subjectivity involved in the assessment of fingerprints. With the methodologies employed for fingerprints sharing parallels to the methodologies employed for vein pattern and surface feature assessment (Black et al., 2014b; Campbell, 2011; Jackson and Black, 2014; Macdonald-McMillan, 2011), it should be borne in mind that this form of evidence is currently opinion level based and not fact based.

Despite this, the approach of the biometric systems can be sought for inspiration in the development of hand feature analysis techniques. This research has attempted to replicate the means by which biometric systems set their threshold, albeit on a smaller scale compared to large commercial biometric databases, by building a database of hand images, from which the vein patterns and other features were quantified. The sample size was 53 individuals, which, was deemed large enough to demonstrate the general overview of data distribution, but it is acknowledged that a larger database is essential to enable robust statistical testing; a requirement for the establishment of this method as a viable forensic method (the application of network analysis to the quantification of vein patterns).

As stated by Cross and Smith (1995), no biometric modality has been proven to be unique, instead biometric systems rely on the assessment of probabilities of a particular combination of features occurring in more than one individual. This is an approach that can be mimicked when assessing vein networks and surface features for forensic use, and it is hoped that the data from this study will enable these probabilities to be realised with additional research.

Using previously collected databases it is possible to assign probabilities to the presence of a particular set of features based on precise statistics, to ensure a logical and robust interpretation of expert evidence (Taroni *et al*., 2001). This form of logical reasoning has been proposed and utilised in the reasoning of forensic evidence, through the production of likelihood ratios, based on probabilities (Aitken et al., 2010; Jackson and Black, 2014; Taroni et al., 2001). The likelihood ratio (LR) model involves the consideration of two specific questions or propositions, and the subsequent ratio between the two probabilities is the LR:

(i) the probability of observing the degree of similarity (or dissimilarity) between two images of hands if they come from the same source; and

(ii) the probability of observing this degree of similarity (or dissimilarity) if the two images of hands come from different sources.

(Campbell, 2011; Champod, 2007).

This practice should be used with caution, as in some cases that have attempted to use LR and probabilities have resulted in a miscarriage of justice (R v Clark (2003), R v T (2010)). It is therefore recommended that the continued development of the methods outlined in this research be conducted in collaboration with an experienced forensic statistician to enable the use of logical reasoning, as just described.

9.3.1 Practical applications in forensic human identification

The method of establishing whether a suspect is the offender seen depicted in images of CSA, has been utilised, presented, and accepted by the UK courts; and has led to a change of plea in 80% of cases performed by the team at CAHId. However, the requirement for all forensic techniques to be supported by robustly tested databases with proven validity and reliability remains.

This study built on previous research regarding quantification of the superficial vein pattern, and progressed a step further by introducing network analysis. This approach has shown how the vein pattern can be quantified in more detail than previous feature count approaches, by considering the topological arrangement of sub-groups of the vein pattern, thus increasing its discriminatory power.

This study has shown that, through manual extraction of vein network data, the method is repeatable, thus validating these methods. During this study, the existing database in CAHId was augmented to include images in a range of conditions; standardised, altered poses and range of image qualities. It is hoped that future studies extend the application of NA for the full database in CAHId, so that robust statistical testing can be conducted, thus enabling the production of likelihood ratios, as well as a resource that can be used as a ‘real time’ comparison database for forensic case work.

Vein pattern information is seldom used alone in cases involving images of CSA, and where possible other forms of anatomical features are utilised. This study has shown how using multiple forms of information can enhance the already discriminative vein network by supplementing with surface anatomical information. Although surface features (termed ‘soft biometric’) do not exhibit all the criteria of a biometric and alone, may not provide grounds for discrimination between two individuals, used in conjunction with other anatomical features has been shown to enhance the discriminatory capacity of anatomical feature analysis (Jain *et al*., 2004a; Lee *et al*., 2008; Spaun and Bruegge, 2008).

The methods shown in chapter 8 demonstrate how support can be drawn from quantified data on multiple anatomical features. It is hoped this resource can be utilised in forensic case work to search for potential matching combinations of features, upon which likelihood ratios can be established and presented with the visual evidence. These LR’s enable the evidence to be contextualised in terms of ‘weight of evidence’ in comparison to other evidence presented in the case, to the jury/layperson.

Having validated forensic methods that can be used in CSA cases is important for several reasons. Firstly, due to the Scot's law of corroboration, meaning that there must be at least two sources of independent evidence to secure a conviction, it can be challenging to convict those accused of sexual crimes, due to lack of evidence, as prosecution evidence may only come from the victim statement (The Scottish Government, 2012). This highlights the importance of physical evidence, such as an image depicting the offence, and the potential weight it holds in the eyes of the jury. Secondly, acquiring witness evidence from a child can be extremely challenging in terms of acquiring reliable evidence and it is a harrowing experience for the victim (Zajac *et al.*, 2013), therefore being able to present other forms of evidence relieves this pressure for the victim.

This research has taken a step further in validating the use of anatomical features and the quantification of the vein network in more detail, however, the scope for more research remains specifically with regard to the issue of the human operator and the extrapolation of likelihood ratios. It is hoped that future research would consider the development of a semi or fully-automated approach, coupled with a more in-depth exploration of the vein network topology; furthermore that case tests be conducted to demonstrate the applicability of logical reasoning by the use of probabilities and LR's.

9.4 Study strengths and weaknesses

The current study boasts strengths in its application to forensic research and casework; however, limitations also exist. Both the strengths and weaknesses are discussed, followed by outlining opportunities for future research and any threat posed to the success of these propositions. All points are summarised in Table 8-7.

Strengths

Database relevant to the general profile of a sex offender

The collection of a database that represents the general profile of child sex offender is useful in terms of its applicability to forensic case work. The general profile was extrapolated from case work performed by the team at CAHId which comprised; Caucasian, male, and between 18 and 40 years of age.

Collection of database images other than in standardised conditions

The current database is the only one known, which holds images in non-standardised conditions for the purposes of comparative research. This valuable resource will enable analysis to be directly related to real forensic case work.

Introduction of network analysis

The introduction of network analysis to the quantification of vein patterns has enabled a more in-depth examination of the vein patterns, by considering component parts of a pattern, other than the number of features. This introductory research was focussed on the development of extracting vein pattern information to enable network analysis to be conducted, and therefore has opened the possibility for this approach to be further explored.

Quantification of multiple features

In the first case of its kind, this research has examined vein network information alongside anatomical surface features for the purposes of quantifying the incidences at which these features occur in combination. This will provide a solid ground for forensic practitioners to compare their findings from forensic case work.

Weaknesses

Image capture surroundings varied due to locational changes

Slight variations in imaging conditions may be attributable to the different imaging locations, due to collection of data at different locations. Due to slight changes in lighting conditions this may have affected the image quality and therefore the level of detail acquired from these images. This was considered as a normal source of variation in the dataset and was borne in mind throughout interpretation of results.

Minor variations in skin colour not investigated

Minor variations in skin colour were not investigated. The ethnicity of participants was recorded; however this is not entirely descriptive of the precise 'colour' of an individual's skin. Anecdotally it was observed that individuals with very fair skin, had a more exposed vein pattern, compared to those with a darker complexion. It would have been beneficial to utilise a skin tone chart, by which the participant could compare their skin colour and select a range within which they felt their skin colour was best described.

Hair data not informative

With hindsight, the data relating to hair would have been recorded differently, to include a scale relating to the density of hair observed. As hair is a universal trait, the presence or absence of it, does not inform of the degree to which it obscures other anatomical features; which was the reason for collecting this data.

Inconsistent Sp position

The semi-pronated position was recorded to show the data loss between a standardised and non-standardised image. The Sp position represents the hand in a functional position, as it is often seen in forensic case images, thus its relevance to the current research. However, this meant that the precise positon was difficult to dictate to the participant, which led to minor variations in the position. It could therefore be argued that comparisons using data from these images were not standardised, however, it was recorded to show a non-standardised positon, and therefore the variation in position met the requirements for the research entirely. Of course, the variations should be, and were, borne in mind when interrupting the data relating to positional changes.

Relatively small database

The overall database was relatively small, after individuals were selected to represent the general profile of a sex offender. This issue was exacerbated by the fact that the vein networks were complex, and thus would have required a much larger database for robust statistical analyses.

A small sample size was also an issue with regard to the inter-observer study for reliability of extracting vein network information. The sample size was small in relation to the number of participants, even smaller were the number of observers within each experience category, therefore making interpretation of statistical analyses challenging. Again, particularly with vein network data, the study would have benefitted from a much larger pool of individuals as well as a larger number of test images. It is also recommended that future studies should expand by utilising more observers, with a both a broad range of experiences, but also with many observer of similar experiences, so that robust statistical analyses can be performed.

Removal of 'directed' vein network information.

The directional information was removed from the final analysis of the vein networks, as the non-directed data was deemed reasonable for the remit of this research; to provide an overview of variation across the database. However for future research to consider a more in-depth examination of the networks, the directional information is available to utilise for all networks considered in this research, thus this may be viewed as an opportunity for future research.

Opportunities for future research

Expansion of network analysis of vein patterns

This study has introduced how network analysis can be employed to assess vein networks. As a preliminary study, the database used was appropriate to introduce the methods, but to fully explore the potential of the methods; a larger database would be required to assess the complex structures of vein networks. It is hoped that the methods proposed in this research will be employed on the extended database within CAHId (contains data relating to >600 individuals).

Indication of 'learning' whilst tracing vein patterns gives rise to potential new study.

There was an indication that a learning process is involved in the extraction of vein network information, and so to explore this fully it is recommended that an extended observer study be conducted, with a larger pool of observers and images.

Development of semi or fully automated software to extract VP

Despite the fact that the introduction of network analysis provides a more in-depth quantification of the pattern, the requirement for a human user to extract the data still remains. To alleviate the inherent error with a human operator would require the development of semi or fully automated software to extract the vein network data from within digital images. This is something that would be interesting to consider in future studies; however it is thought that this would require expertise from a computer science background.

Threats

Downgrading of fingerprints, may lead to emerging techniques facing more boundaries to be admitted into court.

In light of the fingerprint inquiry, fingerprint evidence is now considered as opinion evidence rather than fact. Although it may be assumed that this would impact on existing methods and the development of new forensic techniques, the use of probabilities and LR's allows opinion evidence to be relayed in a logical manner, without being a matter of fact. Therefore, this issue could be seen as both a threat, and an opportunity.

Production of LR's require a statistician

To enable the presentation of vein network and surface feature data to be viable in court, it is suggested that the data provided in this study and from future studies, will enable the production of case specific likelihood ratios and probabilities, which can be used to inform the jury/lay person in a comprehensible manner; this is seen as an opportunity for future research, however, this would require the expertise of a forensic statistician, to ensure this process was carried out correctly.

Development of semi- or fully automated software requires expertise from other disciplines; computing etc.

Although the production of a semi or fully automated system to extract data from digital images is desirable to extend the use of vein networks and surface feature information for forensic purposes, this will require extensive input from computer programmers and software developers.

Table 8-7 Table summarising the results from a SWOT (strengths, weaknesses, opportunities, threats) analysis.

Strengths	**Weaknesses**
• Database relevant to the general profile of a sex offender • Collection of database images other than in standardised conditions • Introduction of network analysis • Quantification of multiple features	• Image capture surroundings varied due to locational changes • Minor variations in skin colour not investigated • Hair data not informative • Inconsistent Sp position • Relatively small database • Removal of 'directed' vein network information.
Opportunities	**Threats**
• Expansion of network analysis of vein patterns • Indication of 'learning' whilst tracing vein patterns gives rise to potential new study, investigating learning. • Development of semi or fully automated software to extract VP	• Downgrading of fingerprints, may lead to emerging techniques facing more boundaries to be admitted • Production of LR's require statistician • Development of semi- or fully automated software requires expertise from other disciplines; computing etc.

10 CONCLUSIONS

This multi-disciplinary research has encompassed methods from anatomy, biometrics, statistical computing and law. In doing so it has addressed the relevant areas involved in the use of human anatomy for forensic identification.

This study has addressed the aims which it set out to achieve in that;

- The methods used to extract vein network and surface feature information have been shown to be reliable by one observer and by several, thus providing support for the use of this approach in a forensic context.

- The overall prevalence and distribution of both vein network features and surface features has been outlined in standardised conditions and in relation to selected biological features, so that this information can be used to compare findings from case work.

- The level of detail lost between standardised images and images of poor quality has been outlined and it was highlighted that hand position significantly affects vein pattern information, but does not have a significant effect on surface features, whereas image quality affected features differently. This information can be relayed by practitioners in support of comparisons between suspect and offender images when they are presented with different levels of quality in forensic investigations.

- Finally it has been shown that a multi-modal approach to assessing an individual's identity based on anatomical is a more discriminatively powerful than a uni-modal approach.

From the results of this research, it is suggested that future case work could consider the following methodology; the anatomical features should be marked up following the methods developed by Meadows (2011), additionally the vein pattern should be marked up as described in section 6.1.2. The surface features (where present, surface features other than those considered in this research should be included) should be entered into a vector, along with the vein network data. This will then allow a search to be conducted across the existing database from this research so that comparisons can be conducted against hundreds of images.

This updated methodology requires marginally more time than the existing method, by introducing several more steps to record the vein network information, however the benefit of being able to quantify all anatomical information together will surpass the time constraints. This improvement will act as a stepping stone to the next level of improvement desired for this technique.

To further enhance the method, and to minimise human error, it is suggested that future studies should consider the development of a semi or fully automated system to extract vein network and surface feature information. Not only would this eliminate human error, but would remove the lengthy procedure of manually extracting information from images. The resulting data output would be relatively similar; a series of quantifiable data points that can be compared to thousands of other image data within a database.

Further exploration of sub-isomorphic analysis would allow for vein network to be identified not only on an exact ‘match’ basis, but would also consider if similarities exist between two networks; thus taking into account potential positional changes or image quality differences.

This research has contributed to the current literature and development of methodology regarding anatomical analysis for forensic purposes. In relation to vein patterns this has been achieved by introducing the method of network analysis to vein pattern quantification, which to the author’s knowledge has not been reported previously. Furthermore, it has been shown that there are benefits in using a multi-modal approach to forensic human identification.

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12 APPENDICES

APPENDIX A: VPP database acquisition. Participant pack

PARTICIPANT INFORMATION SHEET

Title of project: Dorsal hand vein analysis: An aid to forensic human identification.

Principal investigator: Harriet Stratton, Centre for Anatomy and Human Identification

Supervisor: Professor Sue Black, Centre for Anatomy and Human Identification

You have been invited to participate in a research study being conducted in the Centre for Anatomy and Human Identification (CAHID) at the University of Dundee. Your participation is voluntary and you may withdraw consent at any time, without explanation.

Please take your time to read the following information and consider your decision. If you have any further questions, please do not hesitate to contact the principal investigator.

Project summary

The patterns created by the superficial network of veins on the back of the hand have been found to have discriminatory properties. These properties have been exploited by the biometrics industry by using vein patterns as an authenticator to aid identification or exclusion of an individual.

This approach of using vein patterns as an aid to identification or exclusion of an individual was introduced to the forensic science field in 2007 by Professor Black and the National Police Improvements Agency (NPIA) and since then this method has been deemed admissible in U.K. courts.

Although vein pattern recognition is widely accepted in the biometrics industry, it has not yet gained widespread acceptance as a legally admissible form of forensic evidence in international courts.

The aim of this project is to address the admissibility of vein pattern recognition as an internationally reputable forensic method, which is admissible in national and international courts. This will require the production of statistical support for the method from a database of hand images.

Role of participant

As a participant you will be requested to have a series of photographic images taken of the back of your hand to expand the database of hand images already held in CAHID. Images will be taken in visible light, in the following specified hand positions:

Images taken using a high quality camera (at three different resolutions)

- Back of hand (fingers extended)
- Back of hand (fist clenched)
- Back of hand (alternative pose)

Images taken using a low quality, mobile phone camera

- Back of hand (fingers extended)
- Back of hand (fist clenched)
- Back of hand (alternative pose)

Additionally you will be asked to have a short video taken of the back of your hand and a section of your wrist using a vein viewer camera. This uses infra-red light to visualise the veins underneath the skin, and a ‘real-time’ image is recorded by the video camera.

Finally you will be asked to have your body fat percentage measured. This will involve having your height measured before standing on a specially adapted set of weighing scales. According to the manufacturer’s guidelines, if you have a heart pace maker fitted, you are advised to not use these weighing scales.

If you have a pacemaker fitted, you will be offered an alternative method of recording body fat percentage. This will comprise of skin fold thickness measurements.

All image capture and measurements will be carried out in one session and will take a maximum of 10 minutes.

Your participation is voluntary and you may decide to stop being a part of the research study at any time without explanation. You are entitled to take part in all, some or no aspects of the study. Should you wish to omit consent of any part of the data collection, please specify on the supplied consent form.

Exclusion criteria

Participants must be aged over 18 years old

The only perceivable risk in this study is to those fitted with a heart pace maker. The manufacturers of the weighing scales used in this study, advise that those fitted with a pacemaker should not use the scales. If you have a pace maker fitted, I will have to exclude you from this section of the study, and you will be offered an alternative method.

Pregnant women will also be excluded from this aspect of the study, but will also be offered an alternative method.

Confidentiality/Anonymity

The images obtained in this study will only be identifiable to the principal investigator and their supervisors. The data will be stored securely on a password access controlled database and will comply with the Data Protection Act 1998.

Findings from the research may be published in relevant journals and presented at conferences attended by the principal investigator and, or the students supervisor, however no identifiable information will be included in such publications.

For further information about this research please contact:

Harriet Stratton

h.r.stratton@dundee.ac.uk

Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

Professor Sue Black

01382 385776

s.m.black@dundee.ac.uk

Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

The University Research Ethics Committee of the University of Dundee has reviewed and approved this research study.

PARTICIPANT CONSENT FORM

Title of project: Dorsal hand vein analysis: An aid to forensic human identification.

Principal investigator: Harriet Stratton, Centre for Anatomy and Human Identification.

Summary of the research

The aim of this project is to assess the admissibility of vein pattern analysis as an aid to comparing suspect and offender images in a forensic environment.

For further information on the project, please see the supplied participant information sheet or contact the principal investigator.

Are you willing to have the series of photographic images taken of the back of your hand as stated on the information sheet?

Images taken using a high quality camera (at three different resolutions)

- Back of hand (fingers extended)
- Back of hand (fist clenched)
- Back of hand (alternative pose)

Images taken using a low quality, mobile phone camera

- Back of hand (fingers extended)
- Back of hand (fist clenched)
- Back of hand (alternative pose

Are you willing to have the back of your hand filmed with a vein viewer camera?

Are you willing to have a section of your wrist filmed with a vein viewer camera?

Are you willing to have your body fat percentage measured?

By signing below you are agreeing that you have read and understood the Participant Information Sheet and that you agree to take part in this research study.

Participant's signature

Date

Printed name of person obtaining consent

Signature of person obtaining consent

PARTICIPANT QUESTIONNAIRE

Thank you for taking part in this study. The following questions are designed to help the principal investigator and your answers will be appreciated. However, please omit any questions you do not wish to answer.

Your responses will be treated as strictly confidential and will be used only for the purposes stated in the information sheet and in compliance with The University of Dundee Code of Practice for Research Ethics on Human Participants.

Personal Information

Male ☐ Trans-sexual (Female to male) ☐

Female ☐ Trans-sexual (Male to female) ☐

Age: ☐☐

Dominant hand: Left ☐ Ambidextrous ☐

Right ☐

Ethnicity:

White; British ☐ Irish ☐ European ☐

Other. Please specify ___________________________

Black; Caribbean ☐ African ☐ Other. Please specify___________________

Asian; Indian ☐ Pakistani ☐ Bangladeshi ☐

Chinese ☐ Other. Please specify__________________________

Mixed; White & black Caribbean ☐ White & black African ☐

White & Asian ☐ Other. Please specify____________ _______

Body Fat Percentage Measurements

Due to the manufacturer recommendations if you have a heart pacemaker fitted, you will not be able to have your body fat percentage measured using the specially adapted weighing scales and will be excluded from this section of the study.

	Y	**N**
Do you have a heart pace maker fitted?	☐	☐
Are you pregnant?	☐	☐

APPENDIX B: Advertisement for participation in image collection.

From: Harriet Stratton <h.r.stratton@dundee.ac.uk>

Date: Tuesday, 23 October 2012 10:44

To: CLS-Wanted <CLS-Wanted@dundee.ac.uk>

Subject: Participants required for research project: ‘Dorsal Hand Vein Analysis: An Aid to Forensic Human Identification’.

Dear All,

I am a PhD student at the Centre for Anatomy and Human Identification and I would like to invite you to take part in my research project.

My project involves assessing the use of vein pattern recognition, along with other anatomical features found on the back of an individual’s hand, as an aid to identification or exclusion of an individual in a forensic environment.

Description of the research

The use of vein pattern analysis in a forensic case was first introduced by Professor Black and the National Police Improvements Agency in 2007 and since has been deemed admissible in UK courts in a number of high profile criminal cases.

My research aims to assess how reliable features of the vein pattern, and other anatomical features found on the back of the hand, are in the process of identifying or excluding an individual in a forensic case.

This will be done by using a series of photographic images of the back of the hand to produce a set of descriptive statistics that can be used to assess the statistical strength for the method, and therefore assess reliability and subsequent admissibility.

Factors that may affect the visualisation of the veins will also be addressed, such as the percentage of body fat found on an individual and the effect of using a low quality camera.

What would be required of you as a participant?

A series of photographic images will be recorded of the back of the hand, using a digital camera and a mobile phone camera, in several hand positions.

An infra-red ‘Vein viewer’ camera will also be used to record a video of the hand in a series of positions, and you will be asked to have a section of your wrist filmed on this camera.

In addition to this participants will be asked to have their height, weight and body fat percentage recorded.

Consent will be required for each aspect of the project and participants may choose to opt-out of any of the images or measurements.

Participants have the right to cease involvement at any time without explanation. All research will be conducted within the Centre for Anatomy and Human Identification. All information will be strictly confidential and data storage will comply with the Data Protection Act 1998.

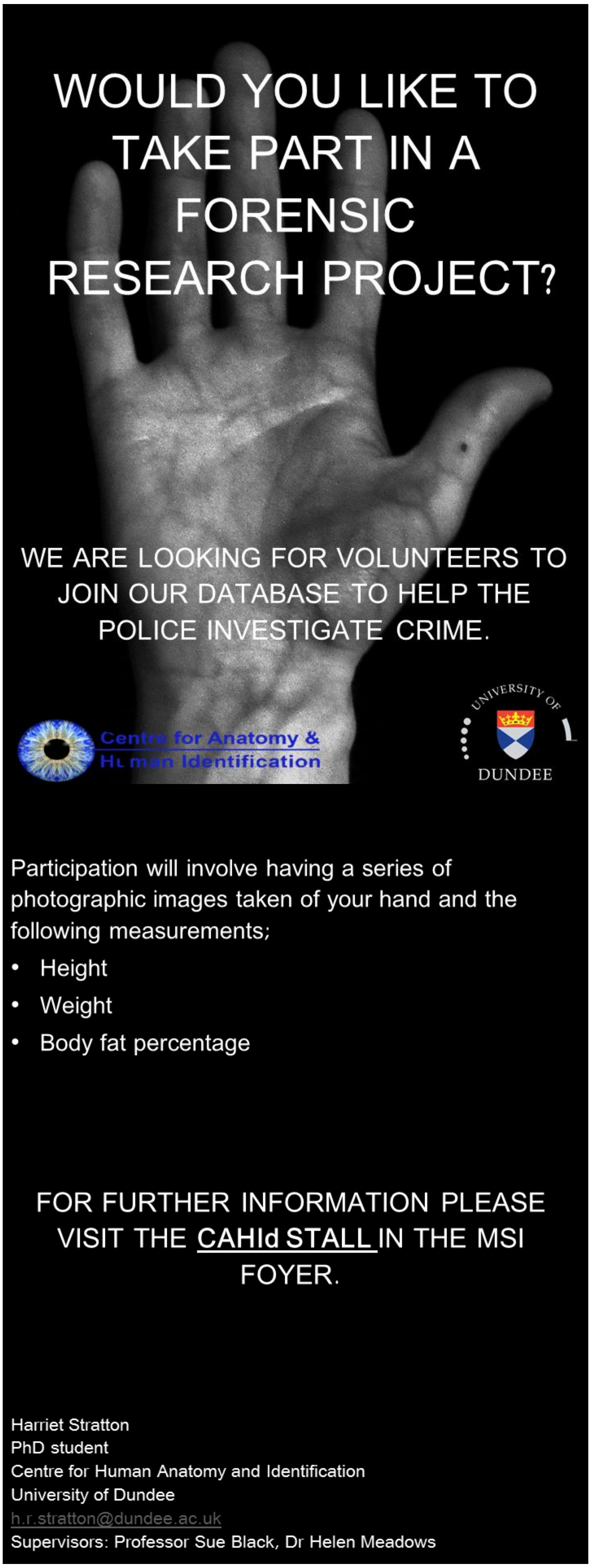
Please note that you will need to declare if you have a pacemaker fitted, as this will affect the way in which your weight and body fat percentage will be measured. There are no reasonably foreseeable risks, harm, discomfort or inconvenience to the participant. No flash photography will be used.

If you are interested in participating in this project and would like more information, please contact me at; h.r.stratton@dundee.ac.uk

Kind regards,
Harriet Stratton

PhD student
Centre for Anatomy and Human Identification
College of Life Sciences
University of Dundee
Dow Street
Dundee DD1 5EH

Flyers used to advertise for participation in image collection at public events.



APPENDIX C: Submitted and accepted ethical approval documents (UREC code 12090).

School of Life Sciences Research Proposal

1. Title of Research Project

Dorsal Hand Vein Analysis: An Aid to Forensic Human Identification.

2. Named Investigators

Name of Principal Investigator **Harriet Stratton**

Phone **01384 384210**

Email **h.r.stratton@dundee.ac.uk**

Postal Address Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

Type of Study **PhD Research Project**

Supervisor **Professor Sue Black**

Phone **01382 385776**

Email **s.m.black@dundee.ac.uk**

Postal Address Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

Second Supervisor **Professor Caroline Wilkinson**

Phone **01382 386324**

Email **c.m.wilkinson@dundee.ac.uk**

Postal Address Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

3. Abstract

The use of superficial vascular patterns is already established as a reliable method for confirming the identity of an individual and is of growing interest in the biometrics industry. Identification or exclusion of an individual by analysing the vein patterns observed in digital images in forensic cases was first introduced in 2007 by Professor Black and the National Police Improvements Agency (NPIA).

Although vein pattern recognition is widely accepted in the biometrics industry, it is a relatively new method in the forensic science industry and is not an internationally recognised method.

The aim of this project is to address the admissibility of vein pattern recognition as an internationally reputable forensic method, which is admissible in national and international courts. This will require the interrogation of the statistical evidence for the method of vein pattern identification from a database of hand images. From the statistical findings a series of likelihood ratios will be produced, which can then be applied to Bayes Theorem.

4. Introduction

Vascular patterns found on an individual's hands have been found to be 'unique' to an individual (Bhattacharyya *et al*., 2010). This property has led to vein patterns being used as a biometric authenticator by the biometrics industry and has become an accepted and reliable method to identify or exclude an individual.

This method of identifying or excluding an individual's identity based on their vein pattern is now being employed forensically, primarily in investigations into child sexual abuse. In these cases, offender images often include the offender's hands and forearms, leaving this section of anatomy the only region available for identification. The vein patterns observed in offender images are being used as an aid to ascertain if a suspect may be the offender by comparison of both suspect and offender images.

The method of comparing offender and suspect vein patterns from photographic images has been deemed admissible in U.K. Courts in high profile cases of child sexual abuse (R v Crossley, (2009); (Meadows, 2011). However this method has not achieved international acceptance as an admissible form of forensic evidence and presently is assessed and carried out on a case by case basis by a small group of expert individuals (R v Crossley, 2009; Meadows, 2011).

In order to enhance the discriminatory power and admissibility of this technique, there is a requirement for strong statistical support.

This project will concentrate on producing the statistical evidence needed for the expert witness to support their findings in court.

5. Aims and Objectives

The primary outcome of the project is to determine the strength of statistical support for vein pattern recognition in a forensic environment.

Aim

The aim is to record and assess the statistical strength for the use of the superficial vascular pattern on the dorsum of the hand as an aid to identification or exclusion of an individual in forensic investigations of child sexual abuse. This will require the (i) production of statistical evidence for the method and the assessment of its viability for forensic application, (ii) assessment of additional anatomical features (for example; freckles, scars, moles and skin pigmentation) as a supplementary tool to enhance the identification or exclusion of an individual.

Objectives

To assess the admissibility of vein pattern analysis as a tool for forensic human identification in forensic investigations.

To assess the discriminative power of the features of a vein pattern in terms of identification.

To assess the discriminative power of additional features observed on the dorsum of the hand (freckles, scars, skin pigmentation etc.).

To investigate how an unfavourable image (analogous to a forensic case image) can affect vein pattern analysis in terms of identification.

To categorise vein patterns to develop the existing identification or exclusion process

To produce a statistical framework that can be relied upon by expert witnesses in court.

6. Literature Review

The pattern created by the network of superficial veins on the dorsum of the hand has been found to be unique to an individual (Bhattacharyya *et al*., 2010). Consequently these patterns are exploited by the biometrics industry as an aid to identify or exclude an individual. The properties of the superficial veins on the dorsum of the hand make them ideal as a biometric authenticator as they do not change over time and are highly resistant to fraud (Lingyu and Leedham, 2006).

The use of vein pattern recognition as a biometric authenticator is attracting interest from the biometric industry (Jain *et al.*, 2007, Lee *et al.*, 2009, Lee and Park, 2009), an example being the Bank of Tokyo's use of vein pattern recognition systems for ATM access.

Current vein pattern recognition biometric systems exploit the interaction of infra-red (IR) light and the deoxygenated haemoglobin found only in venous blood. IR light is more readily absorbed by venous blood than surrounding structures (Cross and Smith, 1995) resulting in an image where vein patterns appear as dark, distinguishable lines. The biometric system then processes the image and creates a binary skeleton. This is then used to compare against other binary images already enrolled on the system to arrive at an identification or exclusion of the individual.

Vein patterns as an identification or exclusion tool in forensic investigations into child sexual abuse was introduced to a U.K. Court in 2007 by Professor Black and the NPIA.

However this method is not internationally recognised as an admissible form of forensic evidence and presently is assessed and carried out by a small group of expert individuals (R v Crossley, 2009; Meadows, 2011).

This project will assess the strength of the admissibility of the existing method for use in forensic investigations, primarily into child sexual abuse. The existing method utilises the vein pattern and additional anatomical features (freckles, moles, scars etc.) observed in offender images as a method to support identification or exclusion of a suspect by manually assessing the observed features from a photographic image. Offender images often only include the offender's hand and forearm, therefore this region of anatomy may be the only identifiable area of the offender.

To assess the reliability and subsequently the admissibility of this method, the production of statistical evidence describing the variability of vein patterns and the occurrence of other variables (freckles, moles, scars etc.) across a population is imperative, as well as investigating other factors which may affect the ability to visualise vein patterns.

This project will concentrate on producing the statistical evidence needed for the expert witness to support their findings in court. This project will build on previous work (Meadows, 2011; (Bellini, 2010) by addressing the statistical power of superficial vein pattern analysis by using the data collected from computer software (Bellini, 2011) along with data from manual tracings where the existing computer software is not capable of analysing lower quality images.

To produce these statistics, a large number of images of the hands of individuals will be collected for statistical analysis. These images will be photographically captured in visible light and in infra-red light with the use of a vein viewer video camera.

7. Contribution to Existing Knowledge

Matching of vein patterns and additional anatomical features is currently employed (R v Crossley 2009, Meadows 2011) and has been deemed admissible by U.K. Courts on a case by case basis. To gain widespread acceptance as a reliable method there is a requirement for the production of statistical evidence in the form of likelihood ratios and the application of Bayes Theorem.

This will enhance the methods credibility to the courts and the jury, as well as helping the jury to understand.

The introduction of a new forensic method in court requires strong statistical support (House of Commons Science and Technology Committee, 2005).

Previous projects have developed a viable manual method and a semi-automated computer software for analysing the images (Meadows, 2011 and Bellini, 2010). There is now a requirement for the discriminative power of these methods to be investigated rigorously with the aim of gaining acceptance in national and international courts.

The features within a vein pattern (for example; bifurcations, branching angles and islands) will be assessed along with additional anatomical features. The aim is to increase the strength of the method by using additional variables (freckles, moles, scars etc.) in conjunction with vein pattern analysis.

Factors which may affect the visualisation and subsequent extraction of a vein pattern by both computer and manual methods will be investigated. This project will assess the effect of skin colour and percentage of body fat on the visualisation of vein patterns and the ability to visualise and trace them repeatedly.

This project will enhance the work already done in this area and further assess the potential for widespread utilisation of this method in the national and international forensic industry.

8. Approach to the research

The statistical power of superficial vein patterns and features within a vein pattern will be addressed. Other anatomical features observed will be investigated for their discriminatory power. These features may include but are not restricted to areas of pigmentation, scars or callouses, knuckle creases, and lunulae.

Participants will be asked to have images taken in a series of hand poses, in visible light. They will be asked to have six photographic images taken in total; three will be taken with a high quality camera; fingers extended, clenched fist, and the hand in an alternative position. The same three images will be taken with a lower quality camera.

In addition to this, participants will be asked to have a video of their veins captured by a vein viewer camera. The vein viewer emits a beam of IR light onto the back of the hand and the anterior section of the wrist to visualise the veins underneath the skin, and a 'real-time' image is recorded by the video camera.

Finally they will be asked to have their body fat percentage measured to assess the effect of the amount of subcutaneous body fat on the ability to visualise the vein patterns on the dorsum of the hand. The body fat percentage of the whole body and for each of the upper limbs individually will be recorded. This information will be used for the assessment of the effect of hand dominance on the body fat percentage of each upper limb. In relation to this, participants will be asked to specify their dominant hand on the participant questionnaire.

Body fat percentage measurements will be carried out using a set of specially adapted bathroom weighing scales, found on the high street. According to the manufacturers guidelines it is advised that individuals fitted with a pacemaker should not use these weighing scales. For this reason I must exclude such individuals from this study. Those fitted with a pacemaker will be offered an alternative method for measuring body fat percentage. This will involve measuring the skinfold thickness from the triceps using skinfold calipers.

I have also chosen to exclude pregnant women from using the specially adapted weighing scales. However they will be offered the opportunity to use skin caliper measurements to record body fat percentage.

All images and measurements will be taken on one occasion.

The study requires images to be taken of individuals after written consent has been granted (appendix 1, 2 and 3).

All images will be processed, stored and analysed within the access controlled Centre for Anatomy and Human Identification at the University of Dundee. All images will be recorded and archived by the principal investigator under the supervision of Professor Sue Black.

9. Participants and Recruitment

Participants will be identified primarily by their willingness to participate in this study. Staff and students will not be approached directly. Staff and students will be contacted through the advertisement of the study by a blanket email (appendix 4). The email will contain information regarding the aspects of the investigation to be carried out and subjects will be asked to contact the principal investigator if they are happy to take part. Individuals already on the existing Institute of Science and Exercise (ISE) database will be contacted for additional image acquisition. A short talk will be presented to undergraduate science classes to advertise to this cohort.

If they are willing to take part participants will be recruited via provision of further information, participant questionnaire and a participant's consent form (appendix 1, 2 and 3). Individuals can then choose to respond or ignore the email. In doing so there is no potential for a relationship of power between the researcher and the potential participant.

Participants will be recruited from the undergraduate students at the University of Dundee and the staff and postgraduate students within the Centre for Anatomy and Human Identification (CAHID).

Participants will also be recruited from the general public through outreach events, and at conferences attended by the principal investigator. Flyers and posters containing brief information on the project will be made available at public engagement events (appendix 5). These flyers and posters will direct participants to gain further information before taking part in the study (appendix 1, 2 and 3)

They will be asked to have photographic images taken in visible light; firstly with a high quality camera; fingers extended, clenched fist, and the hand in an alternative position taken. The same three images will be taken with a lower quality camera.

They will also be asked to have a video of their veins captured by a vein viewer camera, and have their body fat percentage measured using a set of weighing scales. The height of the individual will first be measured, as this information is required to be added manually to the scales. Those fitted with a pacemaker and pregnant women will be offered an alternative method for measuring body fat percentage. This will involve measuring the skinfold thickness using skinfold calipers. Information on hand dominance will be recorded to investigate the effect of hand dominance on the body fat percentage of the upper limbs.

Some individuals from this cohort already exist on the ISE database. Within the terms of the ethical approval for the previous project (Meadows, 2011) in which the ISE database was constructed, these individuals can be called upon for further image acquisition.

The aim is to collect images from upwards of 300 participants.

Principal inclusion criteria

Participants must be:

Aged over 18

Have signed the participant consent form and ticked all applicable boxes on the consent form

Completed the confidential questionnaire

Only when the candidate has fully understood what will be required of them during the research so that they can give informed consent, will they be enrolled into the study.

Principal exclusion criteria

Participants will be excluded from the study if:

Consent forms are returned unsigned or not returned on day of imaging

They have a heart pace maker fitted (not excluded from whole study, only body fat percentage measurements using specially adapted weighing scales).

They are pregnant(not excluded from whole study, only body fat percentage measurements using specially adapted weighing scales)/

Estimates of participant numbers

Maximum of 160 undergraduate students from within the College of Life Sciences

Maximum of 40 individuals from the Centre for Anatomy and Human Identification.

10. Ethical Considerations

Information sheets will be provided giving a full explanation of the project and its intentions. Details of what is required of the participant will also be fully disclosed (appendix 1, 2 and 3). Participants will be provided will full contact procedure and details of the principal investigator and the project supervisor.

Potential Risks

The only perceivable risk in this study is to those fitted with a pace maker. According to the manufacturers guidelines, it is advised that individuals fitted with a heart pace maker should avoid use of the adapted weighing scales. To avoid this risk I will exclude anyone fitted with a heart pace maker.

I have chosen to exclude pregnant women from using the specially adapted weighing scales as it is unknown if they will have an effect on the unborn child.

All other methods used present no reasonably foreseeable risks, harm, discomfort or inconvenience to the participant. No flash photography will be used. Infra-red photography is non-invasive and has no associated health risks.

Potential Benefits

There is no direct benefit to the participant taking part in this study. Individuals are invited to take part on a volunteer basis.

Protection of privacy, anonymity and confidentiality

On agreeing to take part, participants will be assigned a unique participant number to provide anonymity throughout the investigation. Each participant will receive a volunteer pack containing information on the project and a consent form (appendix 1, 2 and 3). The consent form will carry the unique alpha numerical code that identifies and links together the contents of the volunteer pack, without identifying the individual. All consent forms will be kept separate in a locked filing cabinet on university premises. Information will be transferred to and stored in an isolated database.

Identifiable personal information will only be conveyed to others within the legal framework and with the permission of the participant. Access to and storage of the data will comply with the Data Protection Act 1998. Direct access to the database of participant information will be restricted to the principal investigator only under password access control. However information on the database will be restricted by the investigator and may be shared with partners in this project: supervisors, Professor S. Black, Professor C. Wilkinson and Dr H. Meadows, all within the University of Dundee. The participant's decision to allow information to be in the database is voluntary. Information will be removed from the database immediately upon request.

No identifiable information will be shared without explicit consent. Identifying information will be retained for a minimum of 4 years. No identifiable or confidential information will be published in association with this research. Volunteers will be informed in a timely manner if information becomes available that may be relevant to the participants willingness to continue participation in the study.

11. Resources and Costs

The principal investigator is enrolled in a PhD programme at the University of Dundee with the support of a research studentship from the European Commission (ISEC).

12. Dissemination and Outcome

Participants may request to know the outcome of the investigation, in such cases volunteers will receive a brief report on completion of the research. Participants can request such information at any time during or after the study. Findings from the research may be published in relevant journals and presented at conferences attended by the principal investigator and, or the students supervisor.

References

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Kyle, U. G., Bosaeus, I., De Lorenzo, A. D., Deurenberg, P., Elia, M., Gómez, J. M., Heitmann, B. L., Kent-Smith, L., Melchior, J.-C., Pirlich, M., Scharfetter, H., Schols, A. M. W. J. & Pichard, C. 2004a. Bioelectrical impedance analysis—part I: review of principles and methods. Clinical Nutrition, *23*, *1226-1243.*

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Meadows, H. 2011. Limb Vein Pattern Analysis for Human Forensic Identification. *PhD, University of Dundee.*

APPENDIX D: Participant personal information for full dataset.

	URN	AGE	SEX	HEIGHT	WEIGHT	TOTAL BF%	L ARM BF%	R ARM BF%	DOMINANCE	ETHNICITY
1	**004**	28	M	188	66.8	11.7	11.9	10.9	RIGHT	WHITE BRITISH
2	**008**	33	M	184	74.7	15.3	16.3	16.1	RIGHT	WHITE BRITISH
3	**012**	26	M	178	78.6	17.2	15.8	17.8	LEFT	WHITE BRITISH
4	**019**	34	M	185	87.5	21	20.1	18.7	RIGHT	WHITE DUTCH
5	**022**	21	M	192	84.2	15	13.1	13.1	RIGHT	WHITE BRITISH
6	**023**	22	M	184	81	13.8	13.7	13.9	RIGHT	WHITE BRITISH
7	**036**	20	M	175	82.3	21.5	22.3	21	RIGHT	WHITE BRITISH
8	**041**	18	M	180	72.1	17.6	19.4	17.1	RIGHT	WHITE BRITISH
9	**043**	18	M	172	74.9	18	21	18.6	RIGHT	WHITE BRITISH
10	**049**	21	M	193	122.7	25.8	24.5	23.5	RIGHT	WHITE BRITISH
11	**051**	19	M	178	76.9	20.5	23.2	22.3	RIGHT	WHITE BRITISH
12	**053**	21	M	183	79.1	7	10.1	11.2	RIGHT	WHITE BRITISH
13	**072**	19	M	178	82	19.7	22.5	19	RIGHT	WHITE IRISH
14	**073**	18	M	180	75.6	13.8	16.1	13.3	RIGHT	WHITE BRITISH
15	**074**	32	M	171	78.2	20.8	18.1	20.1	RIGHT	WHITE BRITISH
16	**075**	18	M	174	65.9	15.1	19	19.3	RIGHT	WHITE BRITISH
17	**079**	18	M	177	62.2	17.4	21.6	21.6	RIGHT	WHITE BRITISH
18	**081**	31	M	175	100.2	15.7	14.2	15.7	RIGHT	WHITE BRITISH
19	**085**	18	M	167	73.6	16.3	19	15.9	LEFT	WHITE BRITISH
20	**086**	18	M	181	71.1	13.2	17.2	15.4	RIGHT	WHITE BRITISH
21	**090**	21	M	169	80.3	27.1	26.5	24.7	RIGHT	WHITE BRITISH
22	**096**	23	M	168	62.4	17.3	17.2	16.5	RIGHT	WHITE BRITISH
23	**100**	31	M	178	74.9	13.8	14.8	14.9	RIGHT	WHITE BRITISH
24	**103**	21	M	175	70.3	14.4	14.7	14.4	RIGHT	WHITE BRITISH
25	**105**	22	M	185	92.4	23.2	22.6	21	RIGHT	WHITE IRISH
26	**106**	21	M	185	86.9	13.6	16	13.2	AMBIDEXTROUS	MIXED SCOTTISH IRANIAN
27	**107**	21	M	171	70.3	9.9	11.9	13.7	RIGHT	WHITE BRITISH
28	**108**	20	M	176	84.5	17.4	16.3	17	RIGHT	WHITE BRITISH
29	**109**	21	M	187	76.8	18.3	14.6	13.6	RIGHT	WHITE BRITISH
30	**113**	28	M	178	68.1	17.5	15.5	14.5	RIGHT	WHITE BRITISH
31	**114**	21	M	190	84.7	8.4	11.8	11.1	RIGHT	WHITE BRITISH
32	**117**	18	M	177	92.5	22.4	23.7	23.9	RIGHT	WHITE BRITISH
33	**118**	18	M	169	57.5	14.1	18.7	17.3	RIGHT	WHITE BRITISH
34	**119**	18	M	177	57.2	13.5	20	20	RIGHT	WHITE POLISH
35	**122**	28	M	178	91.8	22	16.9	17.7	RIGHT	WHITE BRITISH
36	**124**	22	M	176	76.1	33.3	30.3	27.6	RIGHT	WHITE BRITISH
37	**130**	26	M	175	81.9	15.7	13.2	13.1	AMBIDEXTROUS	WHITE BRITISH
38	**135**	18	M	183	90.2	24.6	26.4	24	RIGHT	WHITE BRITISH
39	**136**	19	M	177	92.8	25.5	29.3	27.3	RIGHT	WHITE BRITISH
40	**140**	18	M	169	64.6	16.9	19	19.1	RIGHT	WHITE BRITISH
41	**141**	19	M	167	62.2	13	17.8	17	LEFT	WHITE BRITISH
42	**142**	20	M	175	91.2	20.2	20.9	20.1	RIGHT	WHITE BRITISH
43	**144**	22	M	181	80.3	22.7	22.5	22	RIGHT	WHITE BRITISH
44	**148**	34	M	176	90.7	24.9	23.3	23.5	RIGHT	WHITE BRITISH
45	**151**	39	M	174	91.3	25	24.8	24.1	RIGHT	WHITE BRITISH
46	**154**	36	M	185	107.2	22.6	20.1	19.6	RIGHT	WHITE EUROPEAN
47	**157**	23	M	175	77.9	15	15.3	14.8	RIGHT	WHITE EUROPEAN
48	**159**	23	M	163	66.4	6.2	9.6	9.3	RIGHT	WHITE AMERICAN
49	**161**	23	M	185	76.3	13.4	14.9	12.9	RIGHT	WHITE BRITISH
50	**163**	20	M	191	82.8	6.6	9.7	11.3	AMBIDEXTROUS	WHITE IRISH
51	**167**	25	M	192	107.3	22.3	21.4	21.5	RIGHT	WHITE BRITISH
52	**170**	19	M	191	88.2	15.2	17.8	16.4	RIGHT	WHITE BRITISH
53	**171**	19	M	184	72.3	14.8	18.6	16.5	RIGHT	WHITE BRITISH

APPENDIX E: R pseudocode for all analysis (full R code available on request)

i. For extracting networks and motifs from raw R files.

ii. for analysis of intra-observer vein pattern data.

iii. for analysis of inter-observer vein pattern data.

iv. for analysis of main vein pattern results

v. for feature combination analysis

R file name: LoadMainDataset.R

- Location of R files is defined > R retrieves data within R files in defined location.
  - (NB: all R files are configured to execute the necessary commands)

R file name: LoadMainDataset.R

- Consistency checks; checks whether the file name and content match from Templates.

R file name: Template.R and Baseline.R

- Creates the ‘HandsPatternsList’ from the information within the R template files
  - (URN, body side, hand position, image quality, user, date of trace, repeat number, network data (source node > target node).

R file name: LoadMainDataset.R

- Create data structures needed for subsequent analysis; a vector is created that contains all information within the R template (each row corresponds to each file).
- Creates networks from the information with the R files.
  - The highest number node is located, an empty network is then created with that number of nodes; the edges and subsequently plotted between the relevant nodes.
- Networks normalised and directionality removed
- Nodes and edges defined
- Motifs defined (complexity of motifs), re-defining motifs as undirected.
- Saves all network information (nodes, edges, intersections, islands (loops), position, and resolution.
- Checks for simple networks
  - Simple networks exist when there are unconnected nodes or nodes connected to themselves.
- Plot motifs and networks to .pdf file.

Main results analysis:

- Checking, identifying and plotting data for islands/loops
- Checking, identifying and plotting data for edges
- Checking, identifying and plotting data for nodes
- Checking, identifying and plotting data for intersections
- Checking, identifying and plotting combination of features

    - Chi2 tests: islands/loops ~ position, intersections ~ position
    - ANOVA's: Nodes ~ Position, Edges ~ Position, Nodes ~ Image quality, Edges ~ Image quality
    - Correlations: Nodes ~ Edges, loops ~ edges, loops ~ nodes, intersections ~ edges, intersections ~ nodes.
- Motif analysis: plotting % of all motif types, by resolution and position.
- Inclusion of surface feature data
- Conditional probabilities for surface feature data

Observer study analysis; checking for isomorphis:

- Upload data from R files
- Extract information from R files
- Define user 1 as HS
- Defines complexity of each network, and image order for each user.
- 'Collapse'; makes the networks undirected.
- Compares two networks
    - checking for differences in the number of edges, how many edges required to add to make two networks isomorphic (if 0 differences, the networks are isomorphic
    - pairwise comparisons
- Checks for intersection, island/loop and motif reproducibility
- Checks for reproducibility depending on network complexity, pairwise comparisons.

R file name: Baseline.R

- Load relevant packages and define working directories
- Defines variables (islands, intersections), functions and plot motifs
    - Removes over-normalised edges

Observer study analysis; checking for isomorphis:

- Compares two networks (check whether removal of 1/2/3/4 link/edges transforms network to be isomorphic to its comparative network).
- Constructs matrix of the number of edges required to remove until networks are isomorphic

R file name: Combination feature analysis.R

- Load working directories
- Plot all components, checks for distribution: edges, nodes, loops, intersections
- Constructs matrix:
    - combines intersection, loop, edges and nodes vectors together
    - defines column names
    - categorises nodes and edges into quantiles; re-defines groups and high, medium, low
    - adds URN, position and side information to vector,
    - defines new column names
    - uploads surface feature data from directory
    - combines SF data with existing vein network vector
- Changes each row of data to string variable.
- Plots frequency of combinations (selecting which columns (features) to include each time,

APPENDIX F: Assessment of network complexity spreadsheet

	Sparse						Intermediate						Dense					
URN	Rnet-work	Rtrace	R:compl ex	R:edges	R:vertice s	Total	Rnet-work	Rtrace	R:compl ex	R:edges	R:vertice s	Total	Rnet-work	Rtrace	R:compl ex	R:edges	R:vertices	Total
004						0			1	1		2	1				1	2
008	1	1	1	1	1	5						0						0
012	1	1	1	1	1	5						0						0
019					1	1	1	1				2			1	1		2
022		1		1	1	3	1		1			2						0
023				1	1	2	1	1	1			3						0
036	1	1	1	1	1	5						0						0
041		1		1	1	3	1		1			2						0
043						0						0	1		1	1	1	4
049			1	1		2	1				1	2						0
051	1	1	1	1	1	5						0						0
053						0						0	1		1	1	1	4
072						0						0	1	1	1	1	1	5
073						0						0	1		1	1	1	4
074						0					1	1	1		1	1		3
075			1			1	1	1		1		3					1	1
079		1			1	2	1					1			1	1		2
081	1		1	1	1	4						0						0
085						0						0	1	1	1	1	1	5
086						0						0	1	1	1	1	1	5
090	1	1	1	1	1	5						0						0
096						0	1				1	2			1	1		2
100	1		1	1	1	4						0						0
103			1			1						0	1	1		1	1	4
105	1	1	1	1	1	5						0						0
106						0						0	1	1	1	1	1	5
107			1	1		2	1					1					1	1
108			1	1	1	3	1					1						0
109			1	1		2	1	1			1	3						0
113			1	1	1	3	1	1				2						0
114			1	1		2	1				1	2		1				1
117				1	1	2						0	1		1			2
118						0						0	1	1	1	1	1	5
119			1			1	1					1		1		1	1	3
122						0						0	1	1	1	1	1	5
124			1	1		2	1				1	2						0
130	1		1	1	1	4						0						0
135				1	1	2	1	1	1			3						0
136	1	1	1	1	1	5						0						0
140			1			1						0	1	1		1	1	4

141					1	1				1		1	1		1			2
142						0		1			1	2			1	1		2
144				1	1	2	1	1				2			1			1
148						0						0	1	1	1	1	1	5
151						0						0	1	1	1	1	1	5
154	1	1		1	1	4						0			1			1
157						0	1	1	1			3				1	1	2
159			1			1						0	1	1		1	1	4
161			1			1						0	1	1		1	1	4
163						0	1	1	1	1		4					1	1
167						0						0	1	1	1	1	1	5
170						0						0	1	1	1	1	1	5
171	1	1	1	1	1	5						0						0

APPENDIX G: R files for vein pattern intra-observer study (see disc at end of thesis)

APPENDIX H: Inter-observer participant pack (vein pattern study)

PARTICIPANT INFORMATION

Title of project: Dorsal hand feature analysis: An aid to forensic human identification.

Principal investigator: Harriet Stratton, Centre for Anatomy and Human Identification.

Summary of the study

The study is concerned with establishing the discriminatory power of the anatomical features seen on the dorsum of the hand. One of the features being investigated are the patterns created by the superficial network of veins.

These patterns are thought to be highly variable, and may therefore enable discrimination between two individuals. The biometrics industry have exploited this inherent variation and used superficial vein pattern analysis to authenticate users of biometric systems for secure access control. Furthermore, vein patterns have been used to include or exclude a suspect in forensic investigations, through the comparison of suspect and offender images of the dorsum of the hand (Meadows, 2011).

This approach has been employed in a number of cases to help secure a conviction or to encourage a change of plea. However, there is still a requirement for strong statistical support to heighten evidential weight of this approach.

The purpose of this research is to ensure the methodology being investigated in this PhD research complies with the admissibility guidelines set out by legal and forensic bodies which outline the need for scientific methodologies to be supported by empirical data to ensure validity and reliability (Association of Forensic Science Providers, 2009; House of Commons Science and Technology Committee, 2005).

Therefore, the aim of this this **inter-observer study** is to address the reliability of the methodology.

What will be expected of you?

Each observer will be provided with 20 images of the dorsum of the hand. The observer will be asked to mark up the vein pattern using the methods developed during this PhD research.

The study will be carried out within the Centre for Anatomy and Human Identification to ensure that all observers perform the study using the same equipment.

Confidentiality/Anonymity

Findings from the research may be published in relevant journals and presented at conferences attended by the principal investigator and, or the students supervisor, however **no identifiable information will be included** in such publications.

There are **no foreseeable risks** in participating in this study. Your participation is voluntary and you can withdraw from this study, without explanation, at any point.

For further information about this research please contact:

Harriet Stratton

h.r.stratton@dundee.ac.uk

Centre for Anatomy and Human Identification

College of Life Sciences

University of Dundee

Dow Street

DD1 5EH

The University Research Ethics Committee of the University of Dundee has reviewed and approved this research study.

PARTICIPANT CONSENT FORM

By signing below you are agreeing that you have **read and understood the participant information sheet** and that you agree to take part in this research study.

___________________________________ __________________

Participant’s signature Date

___________________________________ ______________________________

Printed name of principal investigator Signature of principal investigator

PARTICIPANT QUESTIONNAIRE

Thank you for taking part in this study. The following questions are designed to help the principal investigator during the analysis stages of this study and your answers will be appreciated. However, please omit any questions you do not wish to answer.

Your responses will be treated as strictly confidential and will be used in compliance with The University of Dundee Code of Practice for Research Ethics on Human Participants.

Personal Information

Age:

Occupation:..

Estimation of experience level:

	Level of experience			
Experience category	**None**	**Minimal**	**Moderate**	**Extensive**
Anatomical knowledge				
Hand feature analysis in forensic investigations				
Operation of R© software				
Operation of Adobe® Photoshop®				

Any other relevant information regarding your experience:--

OBSERVER INSTRUCTIONS (see disc at end of thesis)

APPENDIX I: Inter-observer study: R files. (see disc at end of thesis)

APPENDIX J: Full database R files (VP study) (see disc at end of thesis)

APPENDIX K: Intra-observer raw data (SF study)

rep	urn	side	pigm	scar	hair	sat	dom	age	height	weight	total_bf	bf_side
1	23	L	1	1	1	-52	R	22	184	81	13.8	13.7
1	23	R	1	1	1	-77	R	22	184	81	13.8	13.9
2	23	L	1	0	1	-76	R	22	184	81	13.8	13.7
2	23	R	1	1	1	-71	R	22	184	81	13.8	13.9
3	23	L	1	0	1	-68	R	22	184	81	13.8	13.7
3	23	R	1	1	1	-58	R	22	184	81	13.8	13.9
4	23	L	1	0	1	46	R	22	184	81	13.8	13.7
4	23	R	1	1	1	-88	R	22	184	81	13.8	13.9
5	23	L	1	0	1	-79	R	22	184	81	13.8	13.7
5	23	R	1	1	1	-42	R	22	184	81	13.8	13.9
6	23	L	1	0	1	-68	R	22	184	81	13.8	13.7
6	23	R	1	1	1	-60	R	22	184	81	13.8	13.9
7	23	L	1	1	1	-73	R	22	184	81	13.8	13.7
7	23	R	1	1	1	-68	R	22	184	81	13.8	13.9
8	23	L	1	0	1	-51	R	22	184	81	13.8	13.7
8	23	R	1	1	1	-100	R	22	184	81	13.8	13.9
1	41	L	1	0	1	-73	R	18	180	72.1	17.6	19.4
1	41	R	1	0	1	-59	R	18	180	72.1	17.6	17.1
2	41	L	1	1	1	-93	R	18	180	72.1	17.6	19.4
2	41	R	1	0	1	-69	R	18	180	72.1	17.6	17.1
3	41	L	1	0	1	-51	R	18	180	72.1	17.6	19.4
3	41	R	1	0	1	-60	R	18	180	72.1	17.6	17.1
4	41	L	1	0	1	-63	R	18	180	72.1	17.6	19.4
4	41	R	1	0	1	96	R	18	180	72.1	17.6	17.1
5	41	L	1	0	1	56	R	18	180	72.1	17.6	19.4
5	41	R	1	0	1	-54	R	18	180	72.1	17.6	17.1
6	41	L	1	0	1	-77	R	18	180	72.1	17.6	19.4
6	41	R	1	0	1	-48	R	18	180	72.1	17.6	17.1
7	41	L	1	0	1	-56	R	18	180	72.1	17.6	19.4
7	41	R	1	0	1	-63	R	18	180	72.1	17.6	17.1
8	41	L	1	0	1	-70	R	18	180	72.1	17.6	19.4
8	41	R	1	0	1	-65	R	18	180	72.1	17.6	17.1
1	43	L	1	1	1	-57	R	18	172	74.9	18	21
1	43	R	1	0	1	-73	R	18	172	74.9	18	18.6
2	43	L	1	1	1	-62	R	18	172	74.9	18	21
2	43	R	1	0	1	-65	R	18	172	74.9	18	18.6
3	43	L	1	1	1	-51	R	18	172	74.9	18	21
3	43	R	1	0	1	-80	R	18	172	74.9	18	18.6
4	43	L	1	1	1	-100	R	18	172	74.9	18	21
4	43	R	1	0	1	-77	R	18	172	74.9	18	18.6
5	43	L	1	0	1	-57	R	18	172	74.9	18	21
5	43	R	1	0	1	57	R	18	172	74.9	18	18.6
6	43	L	1	1	1	-73	R	18	172	74.9	18	21
6	43	R	1	0	1	-61	R	18	172	74.9	18	18.6
7	43	L	1	1	1	-43	R	18	172	74.9	18	21
7	43	R	1	0	1	-57	R	18	172	74.9	18	18.6
8	43	L	1	1	1	-94	R	18	172	74.9	18	21
8	43	R	1	0	1	-53	R	18	172	74.9	18	18.6
1	49	L	1	1	1	-100	R	21	193	122.7	25.8	24.5
1	49	R	1	0	1	-77	R	21	193	122.7	25.8	23.5
2	49	L	1	0	1	-59	R	21	193	122.7	25.8	24.5
2	49	R	1	0	1	-62	R	21	193	122.7	25.8	23.5
3	49	L	1	0	1	-49	R	21	193	122.7	25.8	24.5
3	49	R	1	0	1	-47	R	21	193	122.7	25.8	23.5
4	49	L	1	0	1	-100	R	21	193	122.7	25.8	24.5
4	49	R	1	1	1	-55	R	21	193	122.7	25.8	23.5
5	49	L	1	0	1	-54	R	21	193	122.7	25.8	24.5
5	49	R	1	1	1	-69	R	21	193	122.7	25.8	23.5
6	49	L	1	0	1	-50	R	21	193	122.7	25.8	24.5
6	49	R	1	0	1	-31	R	21	193	122.7	25.8	23.5
7	49	L	1	0	1	-51	R	21	193	122.7	25.8	24.5
7	49	R	1	0	1	-42	R	21	193	122.7	25.8	23.5
8	49	L	1	0	1	-73	R	21	193	122.7	25.8	24.5
8	49	R	1	0	1	-81	R	21	193	122.7	25.8	23.5
1	74	L	1	1	1	-70	R	32	171	78.2	20.8	18.1
1	74	R	0	0	1	-92	R	32	171	78.2	20.8	20.1
2	74	L	1	1	1	-60	R	32	171	78.2	20.8	18.1
2	74	R	0	0	1	-88	R	32	171	78.2	20.8	20.1
3	74	L	0	1	1	-74	R	32	171	78.2	20.8	18.1
3	74	R	0	0	1	-52	R	32	171	78.2	20.8	20.1
4	74	L	0	1	1	-55	R	32	171	78.2	20.8	18.1
4	74	R	0	0	1	-100	R	32	171	78.2	20.8	20.1
5	74	L	0	1	1	-39	R	32	171	78.2	20.8	18.1
5	74	R	0	0	1	-53	R	32	171	78.2	20.8	20.1
6	74	L	0	1	1	-60	R	32	171	78.2	20.8	18.1
6	74	R	0	0	1	-56	R	32	171	78.2	20.8	20.1
7	74	L	0	1	1	-29	R	32	171	78.2	20.8	18.1
7	74	R	0	0	1	-55	R	32	171	78.2	20.8	20.1
8	74	L	0	1	1	-52	R	32	171	78.2	20.8	18.1
8	74	R	0	0	1	-72	R	32	171	78.2	20.8	20.1
1	75	L	1	1	1	-62	R	18	174	65.9	15.1	19
1	75	R	1	0	1	-64	R	18	174	65.9	15.1	19.3
2	75	L	1	1	1	-50	R	18	174	65.9	15.1	19
2	75	R	1	1	1	-64	R	18	174	65.9	15.1	19.3
3	75	L	1	1	1	-55	R	18	174	65.9	15.1	19
3	75	R	1	0	1	-43	R	18	174	65.9	15.1	19.3
4	75	L	1	1	1	-92	R	18	174	65.9	15.1	19
4	75	R	1	0	1	-96	R	18	174	65.9	15.1	19.3
5	75	L	1	1	1	-41	R	18	174	65.9	15.1	19
5	75	R	1	0	1	-19	R	18	174	65.9	15.1	19.3
6	75	L	1	1	1	-36	R	18	174	65.9	15.1	19
6	75	R	1	0	1	-68	R	18	174	65.9	15.1	19.3
7	75	L	1	1	1	-79	R	18	174	65.9	15.1	19
7	75	R	1	0	1	-69	R	18	174	65.9	15.1	19.3
8	75	L	1	1	1	-79	R	18	174	65.9	15.1	19
8	75	R	1	0	1	-90	R	18	174	65.9	15.1	19.3
1	86	L	0	0	0	-91	R	18	181	71.1	13.2	17.2
1	86	R	1	1	0	-85	R	18	181	71.1	13.2	15.4
2	86	L	0	0	0	-65	R	18	181	71.1	13.2	17.2

2	86	R	1	1	0	-56	R	18	181	71.1	13.2	15.4
3	86	L	0	0	0	-52	R	18	181	71.1	13.2	17.2
3	86	R	1	1	0	-61	R	18	181	71.1	13.2	15.4
4	86	L	0	0	0	-65	R	18	181	71.1	13.2	17.2
4	86	R	1	0	0	-96	R	18	181	71.1	13.2	15.4
5	86	L	0	0	0	-36	R	18	181	71.1	13.2	17.2
5	86	R	1	1	0	-40	R	18	181	71.1	13.2	15.4
6	86	L	0	0	0	-59	R	18	181	71.1	13.2	17.2
6	86	R	1	0	0	-55	R	18	181	71.1	13.2	15.4
7	86	L	0	0	0	-51	R	18	181	71.1	13.2	17.2
7	86	R	1	0	0	-80	R	18	181	71.1	13.2	15.4
8	86	L	0	0	0	-70	R	18	181	71.1	13.2	17.2
8	86	R	1	0	0	-58	R	18	181	71.1	13.2	15.4
1	108	L	0	1	0	-97	R	20	176	84.5	17.4	16.3
1	108	R	1	0	0	99	R	20	176	84.5	17.4	17
2	108	L	1	0	0	-57	R	20	176	84.5	17.4	16.3
2	108	R	1	0	1	-61	R	20	176	84.5	17.4	17
3	108	L	1	0	0	-65	R	20	176	84.5	17.4	16.3
3	108	R	1	0	1	-51	R	20	176	84.5	17.4	17
4	108	L	1	0	0	-60	R	20	176	84.5	17.4	16.3
4	108	R	1	0	1	-68	R	20	176	84.5	17.4	17
5	108	L	1	0	0	46	R	20	176	84.5	17.4	16.3
5	108	R	1	0	1	-43	R	20	176	84.5	17.4	17
6	108	L	1	0	0	-52	R	20	176	84.5	17.4	16.3
6	108	R	1	0	0	-52	R	20	176	84.5	17.4	17
7	108	L	1	0	0	-55	R	20	176	84.5	17.4	16.3
7	108	R	1	0	1	-59	R	20	176	84.5	17.4	17
8	108	L	1	0	0	-69	R	20	176	84.5	17.4	16.3
8	108	R	1	0	1	-70	R	20	176	84.5	17.4	17
1	114	L	0	0	1	-96	R	21	190	84.7	8.4	11.8
1	114	R	1	1	1	-78	R	21	190	84.7	8.4	11.1
2	114	L	0	0	1	-61	R	21	190	84.7	8.4	11.8
2	114	R	1	1	1	-80	R	21	190	84.7	8.4	11.1
3	114	L	0	0	1	-68	R	21	190	84.7	8.4	11.8
3	114	R	1	1	1	-69	R	21	190	84.7	8.4	11.1
4	114	L	0	0	1	-64	R	21	190	84.7	8.4	11.8
4	114	R	1	1	1	65	R	21	190	84.7	8.4	11.1
5	114	L	0	0	1	-46	R	21	190	84.7	8.4	11.8
5	114	R	1	1	1	-50	R	21	190	84.7	8.4	11.1
6	114	L	0	0	1	-54	R	21	190	84.7	8.4	11.8
6	114	R	1	1	1	-59	R	21	190	84.7	8.4	11.1
7	114	L	0	0	1	-72	R	21	190	84.7	8.4	11.8
7	114	R	1	1	1	-54	R	21	190	84.7	8.4	11.1
8	114	L	0	0	1	100	R	21	190	84.7	8.4	11.8
8	114	R	1	1	1	-71	R	21	190	84.7	8.4	11.1
1	117	L	1	0	1	-63	R	18	177	92.5	22.4	23.7
1	117	R	1	1	1	-63	R	18	177	92.5	22.4	23.9
2	117	L	1	1	1	-69	R	18	177	92.5	22.4	23.7
2	117	R	1	1	1	-59	R	18	177	92.5	22.4	23.9
3	117	L	1	0	1	-68	R	18	177	92.5	22.4	23.7

3	117	R	1	0	1	-47	R	18	177	92.5	22.4	23.9
4	117	L	1	1	1	-59	R	18	177	92.5	22.4	23.7
4	117	R	1	0	0	-84	R	18	177	92.5	22.4	23.9
5	117	L	1	0	1	-52	R	18	177	92.5	22.4	23.7
5	117	R	1	0	1	-61	R	18	177	92.5	22.4	23.9
6	117	L	1	0	1	-51	R	18	177	92.5	22.4	23.7
6	117	R	1	0	1	-51	R	18	177	92.5	22.4	23.9
7	117	L	1	0	1	-57	R	18	177	92.5	22.4	23.7
7	117	R	1	0	1	-64	R	18	177	92.5	22.4	23.9
8	117	L	1	0	1	-72	R	18	177	92.5	22.4	23.7
8	117	R	1	0	1		R	18	177	92.5	22.4	23.9
1	119	L	0	0	1	-63	R	18	177	57.2	13.5	20
1	119	R	1	0	1	80	R	18	177	57.2	13.5	20
2	119	L	0	1	1	-69	R	18	177	57.2	13.5	20
2	119	R	1	0	1	57	R	18	177	57.2	13.5	20
3	119	L	0	0	1	-49	R	18	177	57.2	13.5	20
3	119	R	1	0	1	95	R	18	177	57.2	13.5	20
4	119	L	0	0	1	-96	R	18	177	57.2	13.5	20
4	119	R	1	0	1	83	R	18	177	57.2	13.5	20
5	119	L	0	0	1	-35	R	18	177	57.2	13.5	20
5	119	R	1	0	1	-53	R	18	177	57.2	13.5	20
6	119	L	0	0	1	-41	R	18	177	57.2	13.5	20
6	119	R	1	0	1	-46	R	18	177	57.2	13.5	20
7	119	L	0	0	1	-96	R	18	177	57.2	13.5	20
7	119	R	1	0	1	-77	R	18	177	57.2	13.5	20
8	119	L	0	0	1	-40	R	18	177	57.2	13.5	20
8	119	R	1	0	1	-69	R	18	177	57.2	13.5	20
1	124	L	1	1	0	-64	R	22	176	76.1	33.3	30.3
1	124	R	1	0	0	-81	R	22	176	76.1	33.3	27.6
2	124	L	1	1	0	-66	R	22	176	76.1	33.3	30.3
2	124	R	1	1	0	-50	R	22	176	76.1	33.3	27.6
3	124	L	1	1	0	-60	R	22	176	76.1	33.3	30.3
3	124	R	1	0	0	-74	R	22	176	76.1	33.3	27.6
4	124	L	1	1	0	-93	R	22	176	76.1	33.3	30.3
4	124	R	1	0	0	-77	R	22	176	76.1	33.3	27.6
5	124	L	1	0	1	-35	R	22	176	76.1	33.3	30.3
5	124	R	1	0	0	-65	R	22	176	76.1	33.3	27.6
6	124	L	1	0	0	-46	R	22	176	76.1	33.3	30.3
6	124	R	1	0	0	-35	R	22	176	76.1	33.3	27.6
7	124	L	1	0	0	-75	R	22	176	76.1	33.3	30.3
7	124	R	1	0	1	-74	R	22	176	76.1	33.3	27.6
8	124	L	1	0	0	-57	R	22	176	76.1	33.3	30.3
8	124	R	1	0	0	-82	R	22	176	76.1	33.3	27.6
1	130	L	1	1	1	-88	R	26	175	81.9	15.7	13.2
1	130	R	1	1	1	-87	R	26	175	81.9	15.7	13.1
2	130	L	1	1	1	-50	R	26	175	81.9	15.7	13.2
2	130	R	1	0	1	-73	R	26	175	81.9	15.7	13.1
3	130	L	1	1	1	-75	R	26	175	81.9	15.7	13.2
3	130	R	1	1	1	-71	R	26	175	81.9	15.7	13.1
4	130	L	1	1	1	-100	R	26	175	81.9	15.7	13.2

4	130	R	1	1	1	-95	R	26	175	81.9	15.7	13.1
5	130	L	1	1	1	-75	R	26	175	81.9	15.7	13.2
5	130	R	1	1	1	-53	R	26	175	81.9	15.7	13.1
6	130	L	1	1	1	-56	R	26	175	81.9	15.7	13.2
6	130	R	1	1	1	-61	R	26	175	81.9	15.7	13.1
7	130	L	1	1	1	-47	R	26	175	81.9	15.7	13.2
7	130	R	1	1	1	-45	R	26	175	81.9	15.7	13.1
8	130	L	1	1	1	-49	R	26	175	81.9	15.7	13.2
8	130	R	1	1	1	-79	R	26	175	81.9	15.7	13.1
1	144	L	1	0	1	-88	R	22	181	80.3	22.7	22.5
1	144	R	0	0	1	-78	R	22	181	80.3	22.7	22
2	144	L	1	1	1	-70	R	22	181	80.3	22.7	22.5
2	144	R	0	0	1	-65	R	22	181	80.3	22.7	22
3	144	L	1	0	1	-63	R	22	181	80.3	22.7	22.5
3	144	R	0	0	1	-38	R	22	181	80.3	22.7	22
4	144	L	1	0	1	-61	R	22	181	80.3	22.7	22.5
4	144	R	0	0	1	-77	R	22	181	80.3	22.7	22
5	144	L	1	0	1	-57	R	22	181	80.3	22.7	22.5
5	144	R	0	0	1	-51	R	22	181	80.3	22.7	22
6	144	L	1	0	1	-49	R	22	181	80.3	22.7	22.5
6	144	R	0	0	1	-54	R	22	181	80.3	22.7	22
7	144	L	1	0	1	-57	R	22	181	80.3	22.7	22.5
7	144	R	0	0	1	-70	R	22	181	80.3	22.7	22
8	144	L	1	0	1	-67	R	22	181	80.3	22.7	22.5
8	144	R	0	0	1	-100	R	22	181	80.3	22.7	22
1	154	L	0	1	1	-75	R	36	185	107.2	22.6	20.1
1	154	R	0	1	1	-98	R	36	185	107.2	22.6	19.6
2	154	L	1	0	1	-56	R	36	185	107.2	22.6	20.1
2	154	R	0	1	1	-47	R	36	185	107.2	22.6	19.6
3	154	L	0	0	1	-53	R	36	185	107.2	22.6	20.1
3	154	R	0	1	1	-57	R	36	185	107.2	22.6	19.6
4	154	L	0	0	1	71	R	36	185	107.2	22.6	20.1
4	154	R	0	1	1	-95	R	36	185	107.2	22.6	19.6
5	154	L	0	1	1	-57	R	36	185	107.2	22.6	20.1
5	154	R	0	1	1	-76	R	36	185	107.2	22.6	19.6
6	154	L	0	0	1	-76	R	36	185	107.2	22.6	20.1
6	154	R	0	1	1	-50	R	36	185	107.2	22.6	19.6
7	154	L	0	0	1	-58	R	36	185	107.2	22.6	20.1
7	154	R	0	1	1	-50	R	36	185	107.2	22.6	19.6
8	154	L	0	0	1	-69	R	36	185	107.2	22.6	20.1
8	154	R	0	1	1	-83	R	36	185	107.2	22.6	19.6

Contingency tables and R output from Pearson's Chi squared tests for intra-observer study (SF study)

Pigmentation

		0	1
Rep	1	8	22
	2	6	24
	3	8	22
	4	8	22
	5	8	22
	6	8	22
	7	8	22
	8	8	22

```
        Pearson's Chi-squared test

data:  count
X-squared = 0.6089, df = 7, p-value = 0.9989
```

Scar

		0	1
Rep	1	15	15
	2	16	14
	3	20	10
	4	19	11
	5	20	10
	6	22	8
	7	21	9
	8	22	8

```
Pearson's Chi-squared test

data:  count
X-squared = 6.9769, df = 7, p-value = 0.4313
```

Hair

		0	1
Rep	1	6	24
	2	5	25
	3	5	25
	4	6	24
	5	4	26
	6	6	24
	7	4	26
	8	5	25

```
Pearson's Chi-squared test

data:  count
X-squared = 1.1472, df = 7, p-value = 0.9921
```

Breakdown of scar data:

1 & 2	
1	15
2	14

2 & 3	
2	14
3	10

3 & 4	
3	10
4	11

4 & 5	
4	11
5	10

5 & 6	
5	10
6	8

6 & 7	
6	8
7	9

7 & 8	
7	9
8	8

1 & 3	
1	15
3	10

2 & 4	
2	14
4	11

3 & 5	
3	10
5	10

4 & 6	
4	11
6	8

5 & 7	
5	10
7	9

6 & 8	
6	8
8	8

1 & 4	
1	15
4	11

2 & 5	
2	14
5	10

3 & 6	
3	10
6	8

4 & 7	
4	11
7	9

5 & 8	
5	10
8	8

1 & 5	
1	15
5	10

2 & 6	
2	14
6	8

3 & 7	
3	10
7	9

4 & 8	
4	11
8	8

1 & 6	
1	15
6	8

2 & 7	
2	14
7	9

3 & 8	
3	10
8	8

1 & 7	
1	15
7	9

2 & 8	
2	14
8	8

1 & 8	
1	15
8	8

APPENDIX L: Inter-observer study participant pack (SF study)

PARTICIPANT CONSENT FORM

Title of project: Dorsal hand feature analysis: An aid to forensic human identification.

Principal investigator: Harriet Stratton, Centre for Anatomy and Human Identification.

Summary of the study

Surface anatomical features on the dorsum of the hand are used in the comparison of suspect and offender images.

Features include, but are not be limited to; areas of pigmentation, areas of injury e.g. scars and callouses and the presence of hair.

The present study is intended to establish relationships between these features. Specifically, this inter-observer study aims to qualify the reliability of the methods for identifying the features from photographic images. To achieve this, the features are being recorded using binary code (0= feature absent, 1= feature present).

The role of the participant is outlined in detail in the observer instructions, which you have been provided with. Please ensure you have read these and fully understood what is expected of you as a participant.

By signing below you are agreeing that you have read and understood the observer information sheet and that you agree to take part in this research study.

________________________________ _________________

Participant's signature Date

________________________________ _____________________

Printed name of person obtaining consent Signature of person obtaining consent

PARTICIPANT INSTRUCTIONS

DORSAL HAND FEATURE MAPPING: INTER-OBSERVER STUDY

Principal investigator: Harriet Stratton, Centre for Anatomy and Human Identification

Supervisor: Professor Sue Black, Centre for Anatomy and Human Identification

1 Introduction

Surface anatomical features on the dorsum of the hand are used in the comparison of suspect and offender images.

Features include, but are not be limited to; areas of pigmentation, areas of injury e.g. scars and callouses and the presence of hair.

The present study is intended to establish relationships between these features. Specifically, this inter-observer study aims to qualify the reliability of the methods for identifying the features from photographic images. To achieve this, the features are being recorded using binary code (0= feature absent, 1= feature present).

2. Observer instructions

a) Prepare resources

You will need the following items to complete this study;

- Access to Adobe Photoshop
- A digital copy of images and recording sheet

Copy and paste the 15 folders containing the images onto your desktop. Each individual is identified by their unique reference number (URN). Within each folder are images of the right and left hand. A total of 30 images are provided for analysis.

Copy and paste the Excel spread sheet 'Inter observer recording sheet' onto your desktop and rename the file with your initials as a suffix to enable the researcher to identify your data. All data will be anonymised by the researcher on receipt of your data.

For each feature type, a cell is allocated for the binary code you will assign. It also contains a cell to record the hue and saturation values if they have been adjusted (Figure 1).

	A	B	C	D	E	F	G	H	I
1	Date								
2	No.	Side	**URN**	**Pigmentation**	**Scars/Cuts**	**Hair**	**Hue**	**Sat**	**Midtone**
3	1	L	**001**	1	0	1	0	-28	1
4	1	R							
5	2	L							
6	2	R							
7	3	L							
8	3	R							
9	4	L							
10	4	R							
11	5	L							
12	5	R							

Figure 1: Example of recording sheet

b) Feature recording

1. Open the recording sheet and enter the date in the space provided.

2. Open Adobe Photoshop.
3. Open the image you intend to analyse;
    - [File; Open; *locate image folder,* select URN folder; select image from folder; Open].
4. Examine the region of interest for the feature groups outlined in the recording sheet;
    - Area of skin pigmentation
    - Area of injury
    - Hair

The region of interest in this study is defined as the area within the green border in Figure 2: Region of interest defined within the green border

.

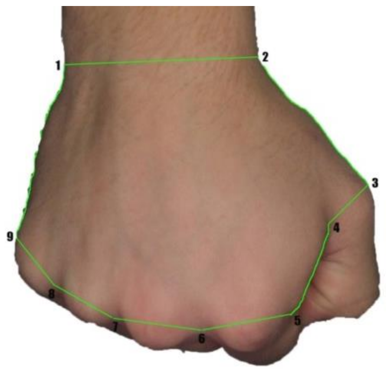
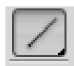


Figure 2: Region of interest defined within the green border

If you are unsure whether a feature is within the region of interest, it may be necessary to physically draw a line across the proximal border (point 1 – 2). This can be done using the line tool in Photoshop.

The line tool is located on the left hand tool bar and is represented by this symbol:



Select the line tool. Using the mouse (or stylus and graphics tablet if you have access to) draw a line from point 1 to 2.

In some images, it may be desirable to adjust the hue and saturation levels to reveal some of the features. This is done using the ‘Adjustments’ tab on the top toolbar.

- Select [Image; Adjustments; Hue/Saturation]. A pop up window will appear. Use the slider to adjust the settings until you can see the features better.
- If you do adjust these settings, record the values in the space provided on the recording sheet.

If a feature is present record it as ‘01’, if there is no feature present, record as ‘00’, in the appropriate space.

This process should be performed for each image (n=30).

APPENDIX M: Raw data from inter-observer surface feature study:

IMAGE ID	OBSERVER	SIDE (L/R)	PIGMENTATION	SCARS	HAIR	HUE	SATURATION
1	A	L	1	0	1	-8	-37
1	A	R	1	1	1	14	-36
1	B	L	1	0	1	7	9
1	B	R	1	1	1	12	-11
1	C	L	1	0	1		
1	C	R	1	1	1		
2	A	L	1	0	1	3	0
2	A	R	1	0	1	-6	19
2	B	L	1	0	1	10	17
2	B	R	1	0	1	12	6
2	C	L	1	0	1		
2	C	R	1	0	1		
3	A	L	0	1	1	3	0
3	A	R	1	0	1	3	0
3	B	L	0	0	1	15	3
3	B	R	1	0	1	26	13
3	C	L	1	0	1		
3	C	R	1	0	1		
4	A	L	1	0	1	-1	1
4	A	R	1	0	1	-9	0
4	B	L	1	0	1	13	4
4	B	R	1	0	1	-6	18
4	C	L	1	0	1		
4	C	R	1	0	1		
5	A	L	0	1	1	-2	0
5	A	R	0	0	1	1	16
5	B	L	1	1	1	0	0
5	B	R	0	0	1	25	13
5	C	L	0	1	1		
5	C	R	0	0	1		
6	A	L	1	1	0	0	0
6	A	R	1	0	1	-8	0
6	B	L	1	0	1	16	7
6	B	R	1	0	1	12	18
6	C	L	1	1	1		
6	C	R	1	0	1		
7	A	L	0	0	0	-1	10
7	A	R	1	0	0	7	3
7	B	L	0	0	1	13	8
7	B	R	1	0	1	0	0
7	C	L	0	0	1		
7	C	R	0	0	1		
8	A	L	1	1	1	0	0
8	A	R	0	0	1	-5	0
8	B	L	1	0	1	-7	7
8	B	R	0	0	1	-10	6
8	C	L	1	0	1		
8	C	R	0	0	1		
9	A	L	0	0	1	5	-24
9	A	R	1	1	1	6	0
9	B	L	0	0	1	26	15
9	B	R	1	0	1	25	17
9	C	L	0	0	1		
9	C	R	1	0	1		
10	A	L	1	0	1	0	0
10	A	R	1	0	1	0	0
10	B	L	1	0	1	20	15
10	B	R	1	0	1	18	14
10	C	L	1	1	1		
10	C	R	1	0	1		
11	A	L	1	0	1	1	1
11	A	R	1	0	1	0	0
11	B	L	0	0	1	13	4
11	B	R	0	0	1	18	8
11	C	L	0	0	1		
11	C	R	0	0	1		
12	A	L	1	0	0	0	0
12	A	R	1	0	0	0	0
12	B	L	1	0	1	10	7
12	B	R	0	0	0	26	14
12	C	L	1	0	1		
12	C	R	1	0	0		
13	A	L	1	0	1	0	0
13	A	R	1	0	1	0	-10
13	B	L	1	1	1	19	11
13	B	R	1	0	1	21	1
13	C	L	1	0	1		
13	C	R	1	0	1		
14	A	L	1	0	1	0	0
14	A	R	0	0	1	0	0
14	B	L	1	0	1	27	-3
14	B	R	0	0	1	34	14
14	C	L	1	0	1		
14	C	R	0	0	1		
15	A	L	0	0	1	0	0
15	A	R	0	1	1	1	0
15	B	L	0	0	1	20	7
15	B	R	0	1	1	24	-3
15	C	L	0	0	1		
15	C	R	0	1	0		

Contingency tables and R output from Pearson's Chi squared tests for inter-observer study (SF study)

Pigmentation

		Status	
		0	1
User	A	9	21
	B	11	19
	C	11	19
	D	8	22

```
Pearson's Chi-squared test

data:  count
X-squared = 1.0256, df = 3, p-value = 0.795
```

Scars

		Status	
		0	1
User	A	23	7
	B	26	4
	C	25	5
	D	19	11

```
Pearson's Chi-squared test

data:  count
X-squared = 5.4958, df = 3, p-value = 0.1389
```

Hair

		Status	
		0	1
User	A	5	25
	B	1	29
	C	2	28
	D	5	25

```
Pearson's Chi-squared test

data:  count
X-squared = 4.3997, df = 3, p-value = 0.2214

Warning message:
In chisq.test(count) : Chi-squared approximation may be incorrect
```

APPENDIX N: Raw data for surface feature main results.

Pigmentation

	c high	**sp high**
0	27.4	25.5
1	72.6	74.5
excl		1

Chi-squared test for given probabilities

data: count

X-squared = 0.0245, df = 1, p-value = 0.8755

	c med	**sp med**
0	53.6	41.5
1	46.2	58.5

Chi-squared test for given probabilities

data: count

X-squared = 1.445, df = 1, p-value = 0.2293

	c low	**sp low**
0	52.8	42.5
1	47.2	57.5
excl		1

Chi-squared test for given probabilities

data: count

X-squared = 1.0133, df = 1, p-value = 0.3141

Scars

	c high	**sp high**
0	56.6	55.7
1	43.4	44.3

Chi-squared test for given probabilities

data: count

X-squared = 0.0092, df = 1, p-value = 0.9234

	c med	**sp med**
0	62.3	63.2
1	37.7	36.8

Chi-squared test for given probabilities

data: count

X-squared = 0.0109, df = 1, p-value = 0.917

	c low	**sp low**
0	79.2	73.6
1	20.8	26.4
	1	1

Chi-squared test for given probabilities

data: count

X-squared = 0.6644, df = 1, p-value = 0.415

Hair

	c high	sp high
0	24.5	22.6
1	75.5	77.4

Chi-squared test for given probabilities

data: count

X-squared = 0.0236, df = 1, p-value = 0.8779

	c med	sp med
0	25.5	21.7
1	74.5	78.3

Chi-squared test for given probabilities

data: count

X-squared = 0.0945, df = 1, p-value = 0.7585

	c low	sp low
0	44.3	49.1
1	55.7	50.9
	1	1

Chi-squared test for given probabilities

data: count

X-squared = 0.2161, df = 1, p-value = 0.642

Comparison of resolution: in same hand position

CLENCHED

Pigmentation		Scars		Hair	
Resolu-tion	Present	Resolution	Present	Resolution	Present
High	72.6	High	43.4	High	75.5
Medium	46.2	Medium	37.7	Medium	74.5
Medium	46.2	Medium	37.7	Medium	74.5
Low	47.2	Low	20.8	Low	55.7
High	72.6	High	43.4	High	75.5
Low	47.2	Low	20.8	Low	55.7

pigm			
	high	med	low
high	0	0.01543*	0.02031*
med		0	0.9176
low			0
scar			
	high	med	low
high	0	0.5268	0.004793*
med		0	0.0213*
low			0
hair			
	high	med	low
high	0	0.9349	0.08388
med		0	0.09043
low			0

SEMI-PRONATED

Pigmentation		Scars		Hair	
Resolution	Present	Resolution	Present	Resolution	Present
High	74.5	High	44.3	High	77.4
Medium	58.5	Medium	36.8	Medium	78.3
Medium	58.5	Medium	36.8	Medium	78.3
Low	57.5	Low	26.4	Low	50.9
High	74.5	High	44.3	High	77.4
Low	57.5	Low	26.4	Low	50.9

pigm			
	high	med	low
high	0	0.1653	0.139
med		0	0.926
low			0
scar			
	high	med	low
high	0	0.4049	0.03327*
med		0	0.1908
low			0
hair			
	high	med	low
high	0	0.9425	0.01931*
med		0	0.01593*
low			0

APPENDIX O: Feature combination vector.

	Ints.	Loops	Edges	Nodes	Pigm	Scar	Hair
4 L	TRUE	TRUE	M	M	1	0	1
4 R	FALSE	TRUE	M	M	0	0	1
8 L	FALSE	TRUE	L	L	1	1	1
8 R	TRUE	TRUE	M	M	0	1	1
12 L	FALSE	FALSE	H	H	1	1	1
12 R	TRUE	FALSE	M	M	0	1	1
19 L	FALSE	FALSE	H	H	0	1	1
19 R	FALSE	FALSE	M	M	0	0	1
22 L	TRUE	TRUE	L	L	1	0	1
22 R	FALSE	FALSE	M	M	1	0	1
23 L	FALSE	TRUE	M	M	1	1	0
23 R	FALSE	TRUE	M	M	1	1	1
36 L	FALSE	FALSE	L	L	1	1	0
36 R	FALSE	FALSE	M	M	1	0	0
41 L	TRUE	TRUE	L	L	1	0	1
41 R	FALSE	TRUE	L	M	1	0	1
43 L	FALSE	FALSE	M	M	1	1	1
43 R	FALSE	TRUE	M	M	1	0	1
49 L	FALSE	TRUE	M	M	1	0	1
49 R	TRUE	FALSE	M	M	1	0	1
51 L	FALSE	FALSE	M	M	1	0	1
51 R	FALSE	FALSE	M	M	1	1	1
53 L	TRUE	FALSE	M	M	0	0	1
53 R	FALSE	TRUE	M	M	1	0	1
72 L	FALSE	FALSE	H	H	0	1	1
72 R	TRUE	TRUE	L	L	0	0	1
73 L	TRUE	FALSE	L	L	0	0	1
73 R	FALSE	TRUE	M	M	0	0	1

74 L	TRUE	FALSE	L	L	1	1	1
74 R	FALSE	TRUE	L	L	0	0	1
75 L	TRUE	TRUE	L	L	1	1	0
75 R	FALSE	FALSE	L	L	1	0	1
79 L	FALSE	TRUE	M	M	1	1	0
79 R	FALSE	TRUE	H	H	1	1	1
81 L	FALSE	FALSE	H	H	0	0	1
81 R	FALSE	FALSE	M	L	1	0	1
85 L	FALSE	FALSE	M	M	1	1	1
85 R	FALSE	TRUE	H	H	1	0	1
86 L	TRUE	FALSE	L	L	0	1	0
86 R	TRUE	TRUE	M	H	1	1	0
90 L	FALSE	FALSE	L	M	1	1	0
90 R	FALSE	FALSE	L	L	0	1	0
96 L	FALSE	TRUE	L	L	1	0	1
96 R	TRUE	TRUE	M	M	1	0	0
100 L	FALSE	FALSE	M	M	0	0	1
100 R	FALSE	FALSE	M	M	0	1	1
103 L	FALSE	FALSE	H	M	1	1	0
103 R	FALSE	FALSE	M	M	1	1	0
105 L	FALSE	FALSE	L	L	1	1	1
105 R	FALSE	FALSE	M	L	1	0	1
106 L	FALSE	FALSE	M	M	1	1	1
106 R	TRUE	TRUE	L	L	0	1	1
107 L	FALSE	FALSE	H	H	1	0	1
107 R	FALSE	FALSE	H	H	1	0	1
108 L	FALSE	FALSE	L	L	1	0	0
108 R	TRUE	FALSE	M	L	0	0	0
109 L	TRUE	TRUE	M	H	1	0	1
109 R	FALSE	FALSE	M	M	1	0	1
113 L	FALSE	FALSE	H	H	1	0	1

113 R	TRUE	FALSE	M	M	1	0	1
114 L	FALSE	FALSE	L	M	0	0	1
114 R	FALSE	FALSE	L	M	1	1	1
117 L	TRUE	FALSE	M	M	1	0	1
117 R	FALSE	TRUE	M	M	1	0	0
118 L	TRUE	TRUE	M	M	1	1	0
118 R	FALSE	TRUE	L	L	1	0	0
119 L	FALSE	FALSE	M	M	0	0	1
119 R	FALSE	FALSE	L	L	1	0	1
122 L	TRUE	FALSE	L	M	1	0	0
122 R	FALSE	TRUE	M	M	1	0	0
124 L	TRUE	FALSE	M	M	1	0	0
124 R	FALSE	FALSE	M	M	1	0	0
130 L	FALSE	FALSE	M	M	1	1	1
130 R	TRUE	FALSE	M	M	1	1	1
135 L	FALSE	FALSE	M	M	0	1	1
135 R	FALSE	FALSE	M	M	0	1	1
136 L	FALSE	FALSE	M	M	1	0	1
136 R	FALSE	FALSE	H	H	1	1	0
140 L	TRUE	FALSE	L	L	0	0	1
140 R	FALSE	FALSE	L	L	1	1	1
141 L	FALSE	FALSE	M	M	1	0	1
141 R	FALSE	TRUE	L	L	1	0	1
142 L	TRUE	FALSE	L	L	1	0	1
142 R	FALSE	FALSE	L	L	1	0	1
144 L	FALSE	FALSE	L	L	1	0	1
144 R	FALSE	TRUE	M	M	1	0	1
148 L	FALSE	FALSE	H	H	1	0	1
148 R	FALSE	TRUE	H	H	1	1	1
151 L	FALSE	FALSE	M	L	1	1	1
151 R	TRUE	TRUE	M	M	1	1	1

154 L	FALSE	FALSE	H	H	0	0	1
154 R	FALSE	FALSE	L	L	1	1	1
157 L	TRUE	TRUE	M	H	0	0	1
157 R	TRUE	TRUE	L	M	0	1	1
159 L	FALSE	FALSE	L	L	0	1	1
159 R	FALSE	FALSE	L	L	0	1	1
161 L	FALSE	TRUE	M	M	1	1	0
161 R	TRUE	TRUE	M	M	1	0	0
163 L	FALSE	TRUE	M	M	1	1	0
163 R	TRUE	TRUE	H	M	1	1	1
167 L	FALSE	TRUE	M	M	1	0	1
167 R	FALSE	TRUE	L	L	1	0	1
170 L	FALSE	TRUE	M	L	1	1	0
170 R	TRUE	TRUE	M	M	1	1	1
171 L	TRUE	TRUE	L	L	0	0	1
171 R	FALSE	FALSE	H	H	1	0	1

APPENDIX P: Supporting documents

Conference abstract submissions in relation to this research:

'Dorsal hand feature analysis: An aid to forensic human identification'. British Association for Human Identification, winter meeting, December 2012. Manchester. Oral presentation.

'Superficial vein pattern analysis: an aid to forensic human identification'. College of Life Sciences, University of Dundee, October 2013. Poster presentation.

'The application of network analysis to superficial veins of the hand: an aid to forensic human identification'. Scottish Institute for Policing Research Conference, November 2013. Poster presentation.

'Dorsal hand feature analysis: An aid to forensic human identification'. British Association for Human Identification, winter meeting, December 2013, Manchester. Poster presentation.

'Dorsal hand feature analysis: An aid to forensic human identification'. Scottish Student Forensic Research inaugural symposium, Glasgow, March 2014. Poster presentation.

Awards gained for work related to this research:

British Association for Human Identification, 1st prize for student poster. December 2013.

Scottish Student Forensic Research, 1st prize for poster. March 2014.